Visualizing Text Sentiment

sic parvis magna

VisSoft 2016

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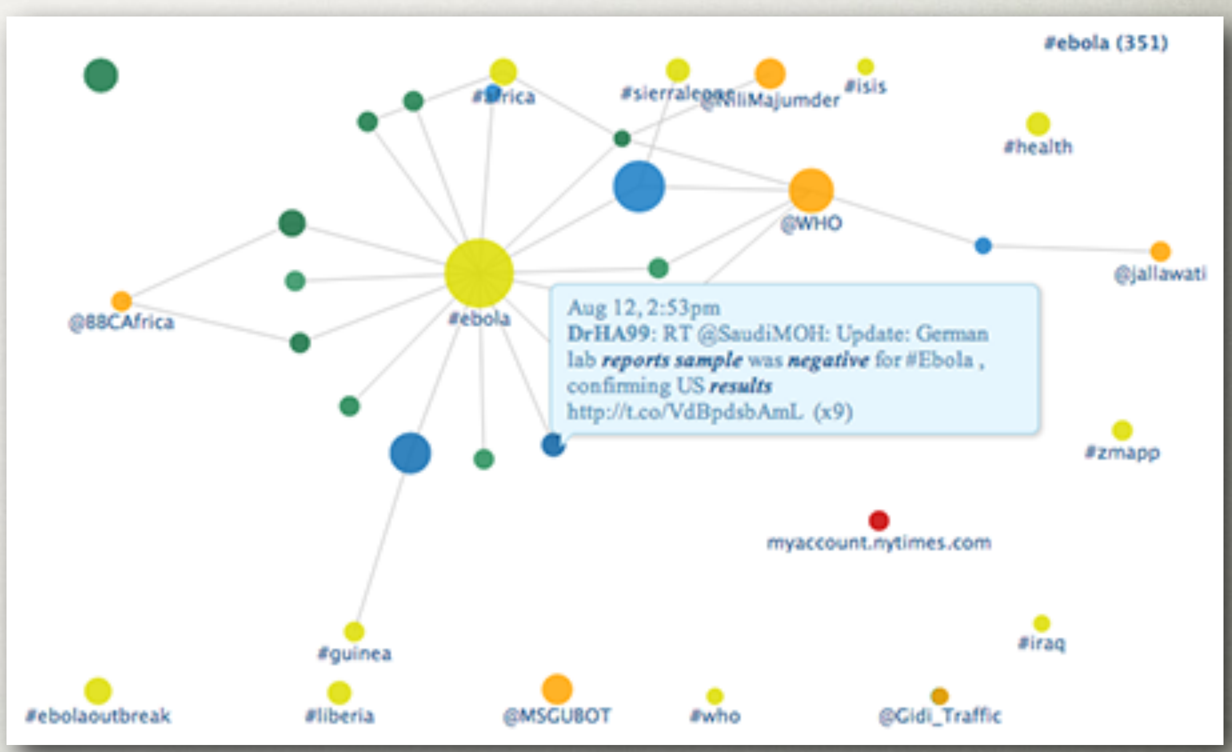
NC STATE UNIVERSITY

Visualization

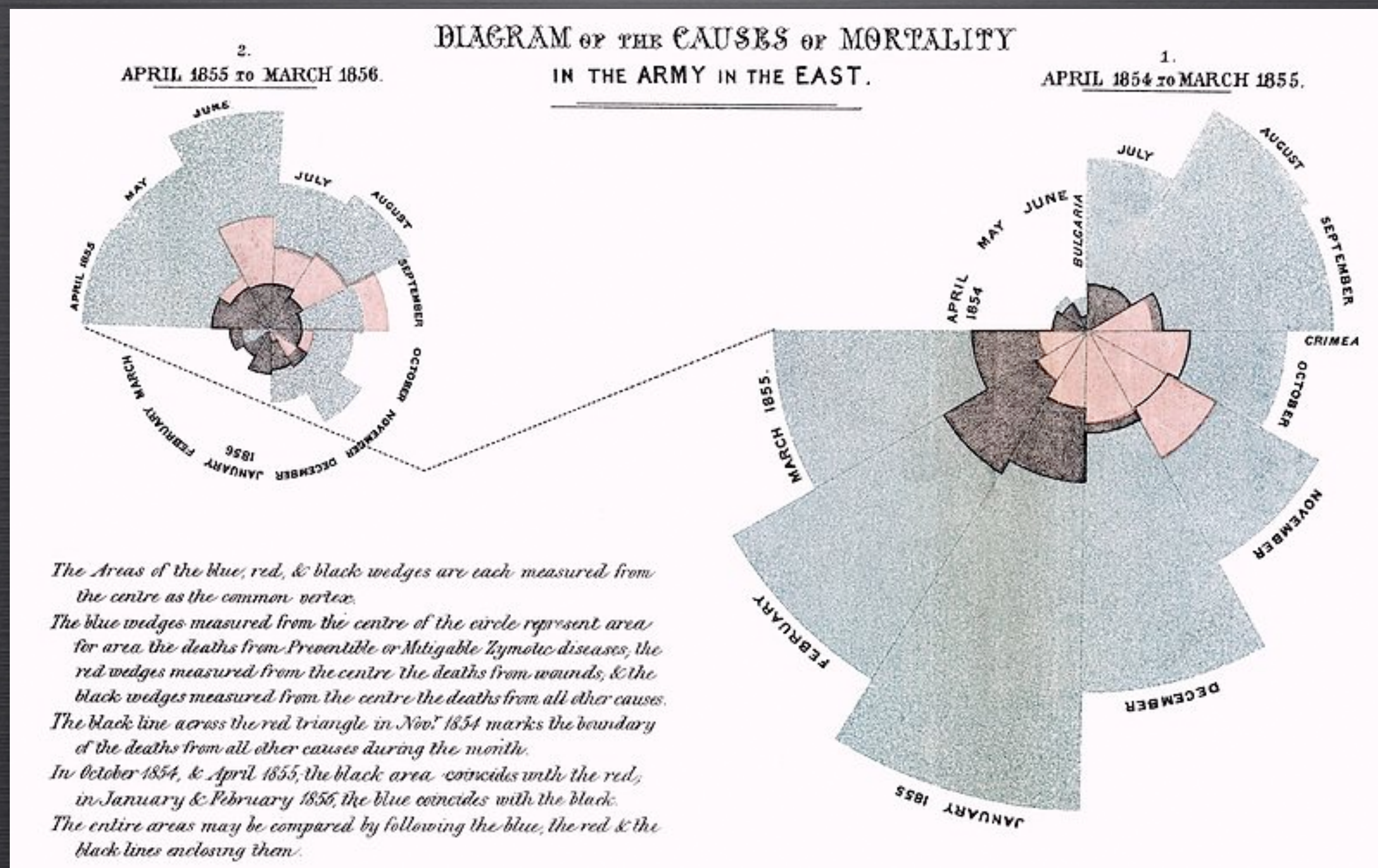
- Harness viewer's strengths
  - human visual system
  - pattern recognition capabilities
  - domain expertise
  - understanding context
  - ability to manage ambiguity
- Collaboration between viewer and computer
  - Enhance each participant's individual strengths
  - Share initiative to offset their weaknesses



Tweet affinity graph:
tweet property → hue, *frequency* → size, *edges* → affinity, *proximity* → similarity

Data courtesy Twitter, Inc.
go.ncsu.edu/tweet-viz

Nightingale's Rose Chart



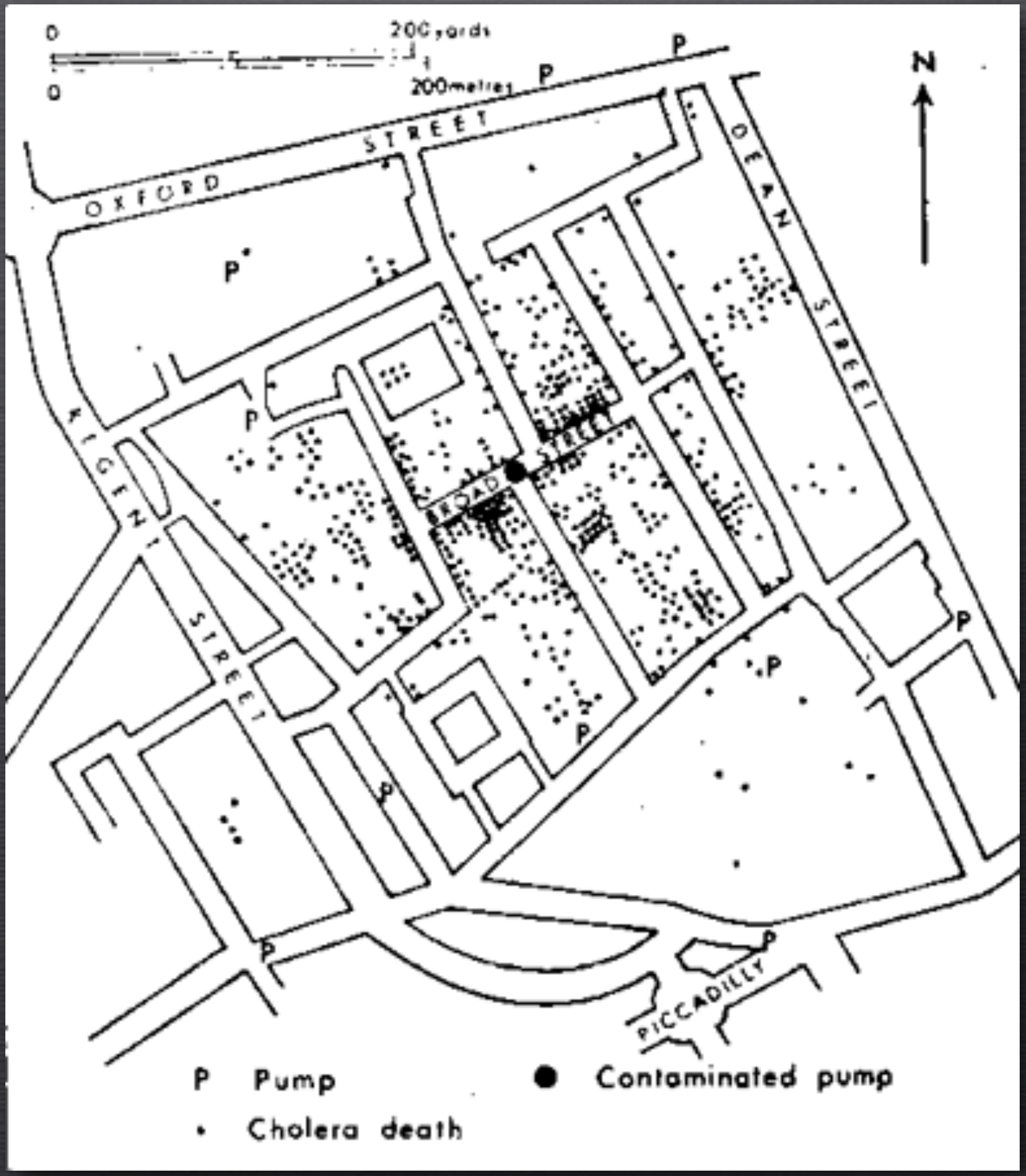
Rose or Coxcomb chart of causes of death during the Crimean War (1854–1855):

month → wedge; **number of deaths** → area;

type of mortality → hue (blue: preventable; pink: wounds; black: other)

Data courtesy understandinguncertainty.org/node/213

Dot Map

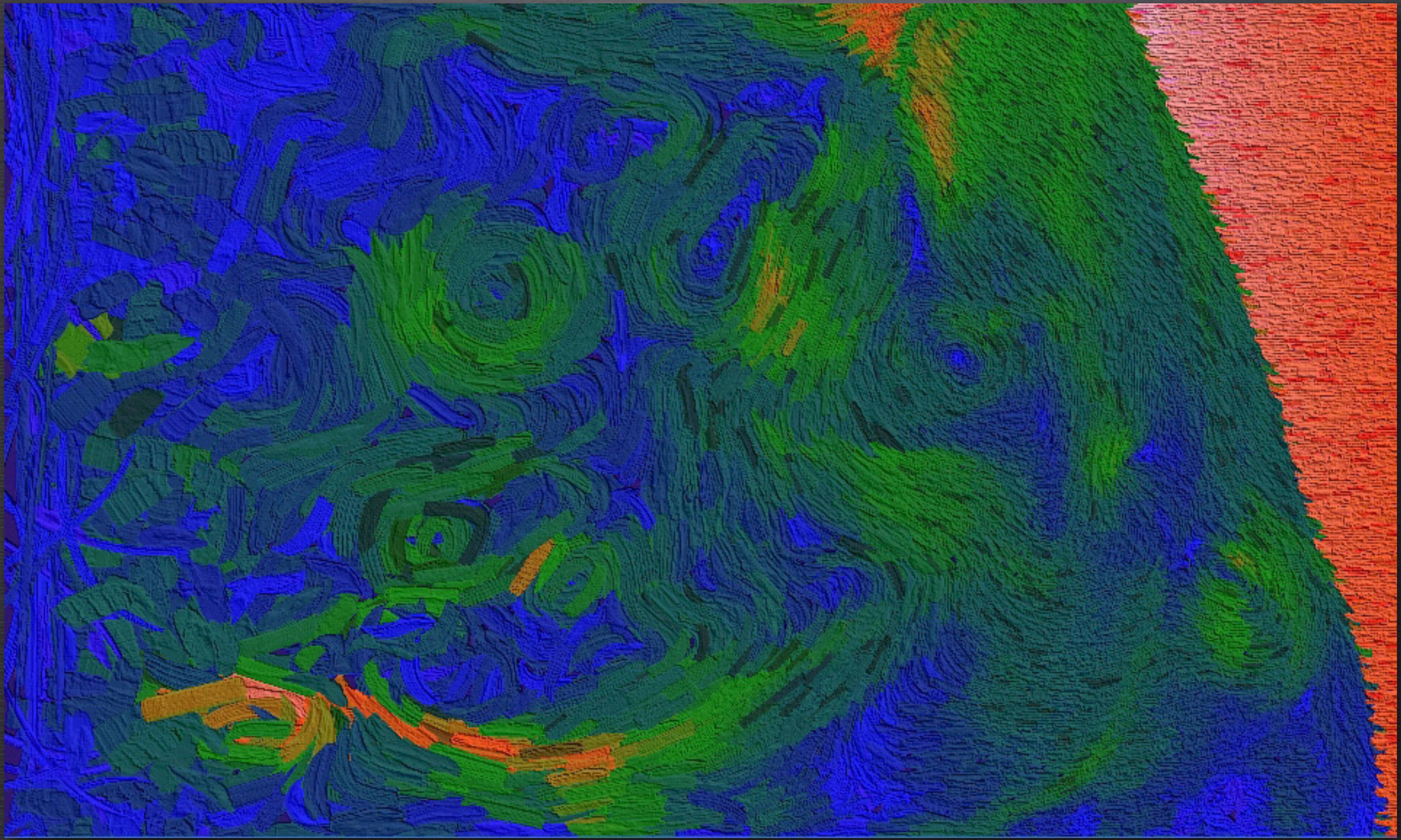


John Snow's cholera map (1854):

Cholera Patient → dot

Data courtesy www.ncgia.ucsb.edu/pubs/snow/snow.html

Painterly Visualization



Painterly visualization of a simulated supernova collapse:

pressure → luminance, **velocity** → hue, **flow direction** → orientation

Data courtesy Dr. Jon Blondin, Astrophysics, NCSU

Tateosian et al. "Engaging Viewers Through Nonphotorealistic Visualizations," NPAR 2007, pp. 93–102.

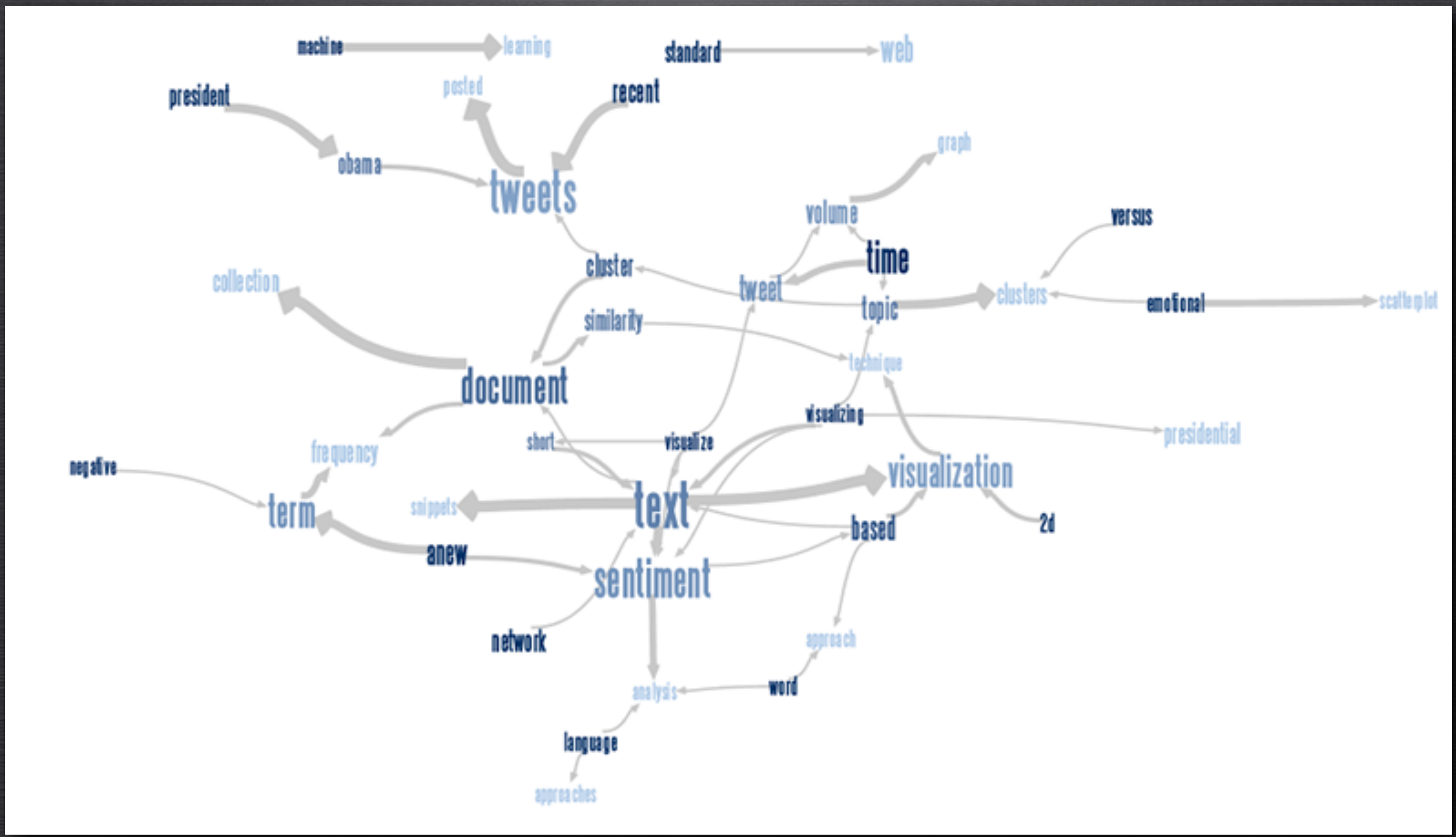
Tag Cloud

Wordle tag cloud:

term → text, term frequency → size

www.wordle.net

Phrase Nets

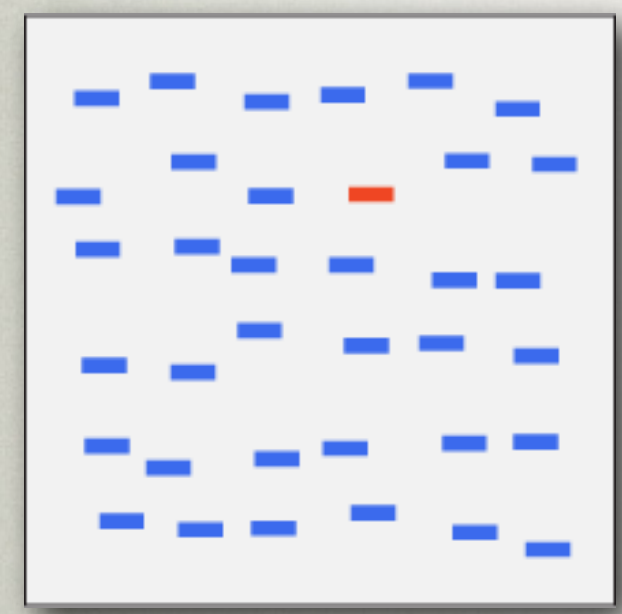


Phrase nets:

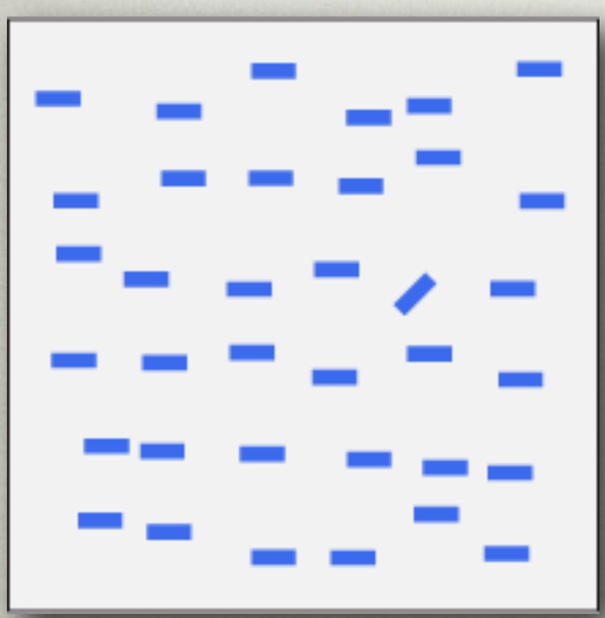
term frequency → size, links → neighbour relationship

www-958.ibm.com/software/analytics/manyeyes/

"Preattentive" Features



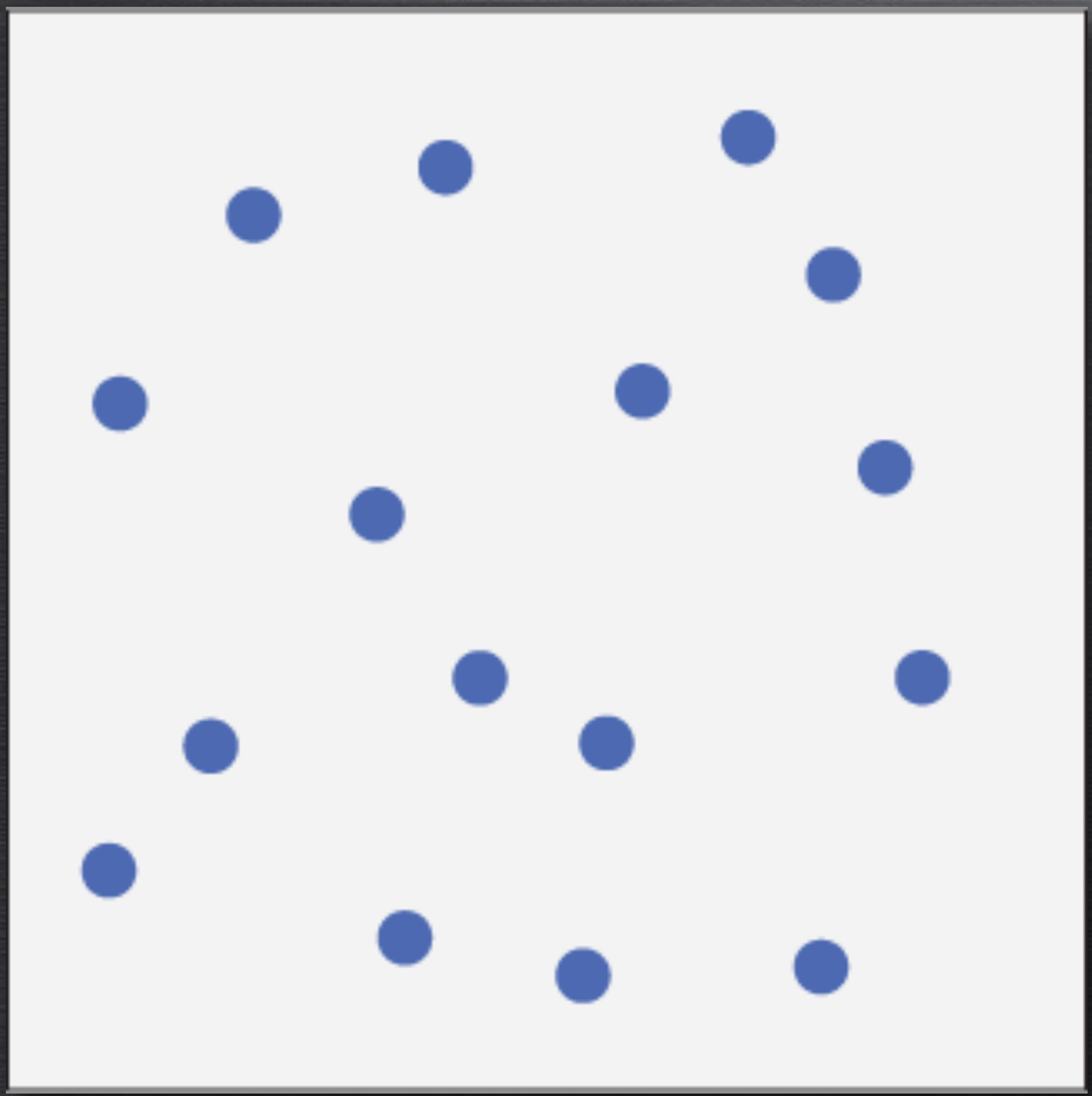
Hue



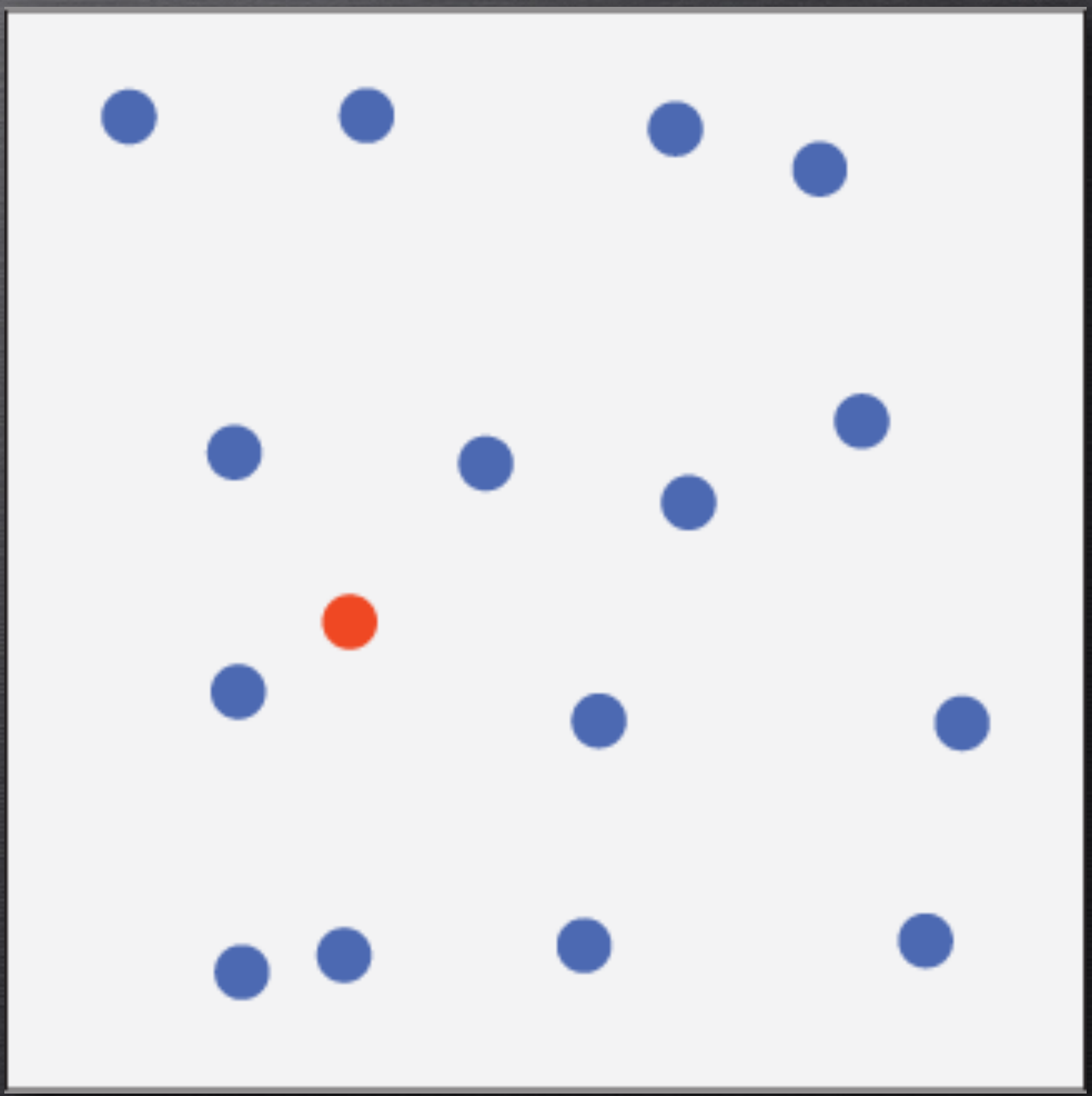
Orientation

- Basic visual features are detected by our low-level visual system
  - detection is rapid, usually in one "glance" of 100–250 msec
  - can determine presence, absence, amount
  - unique features capture our focus of attention
- Initially proposed as an automatic, bottom-up phenomena
  - Treisman's feature map theory
- Revised to include bottom-up and top-down influence
  - Wolfe's guided search

Hue Target



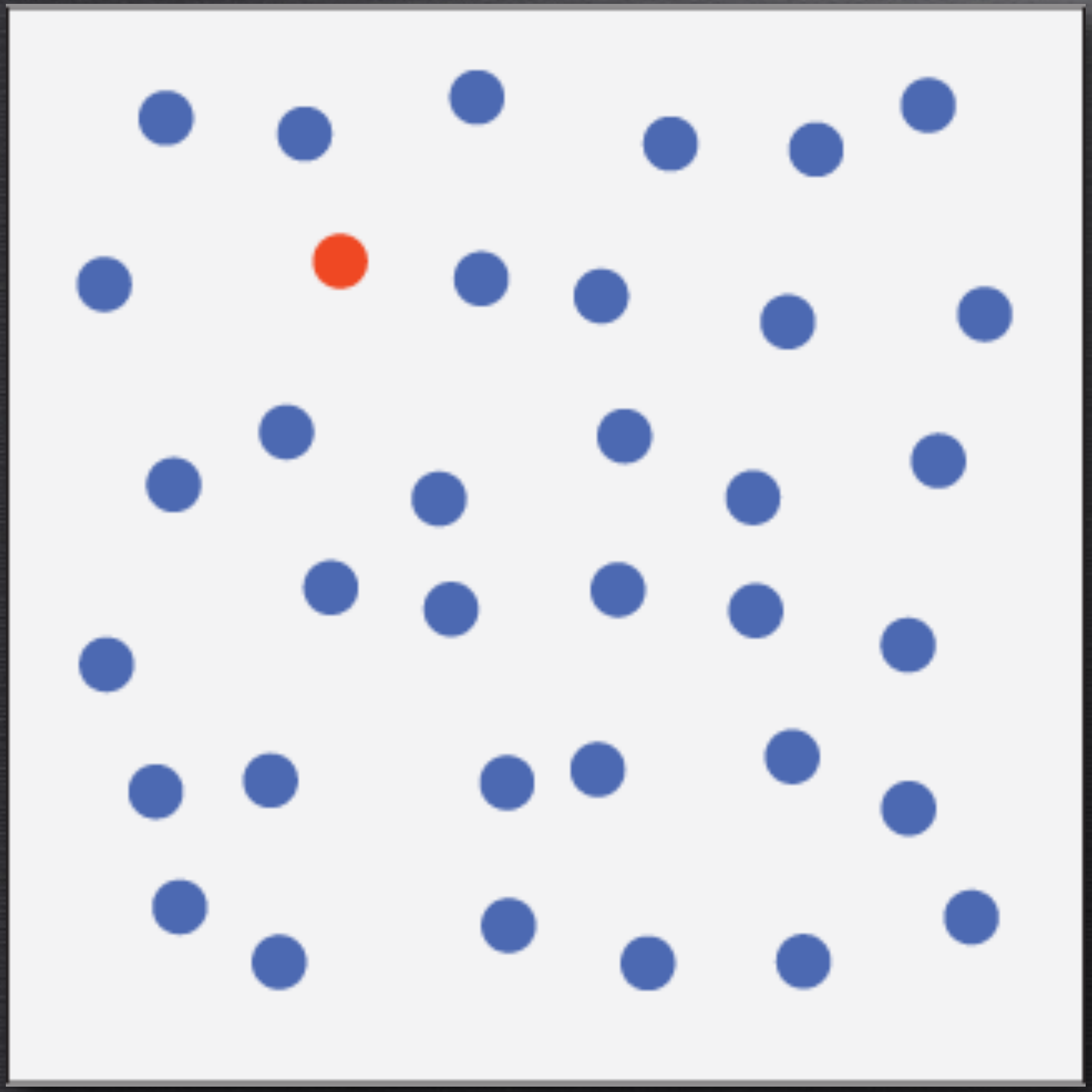
Absent



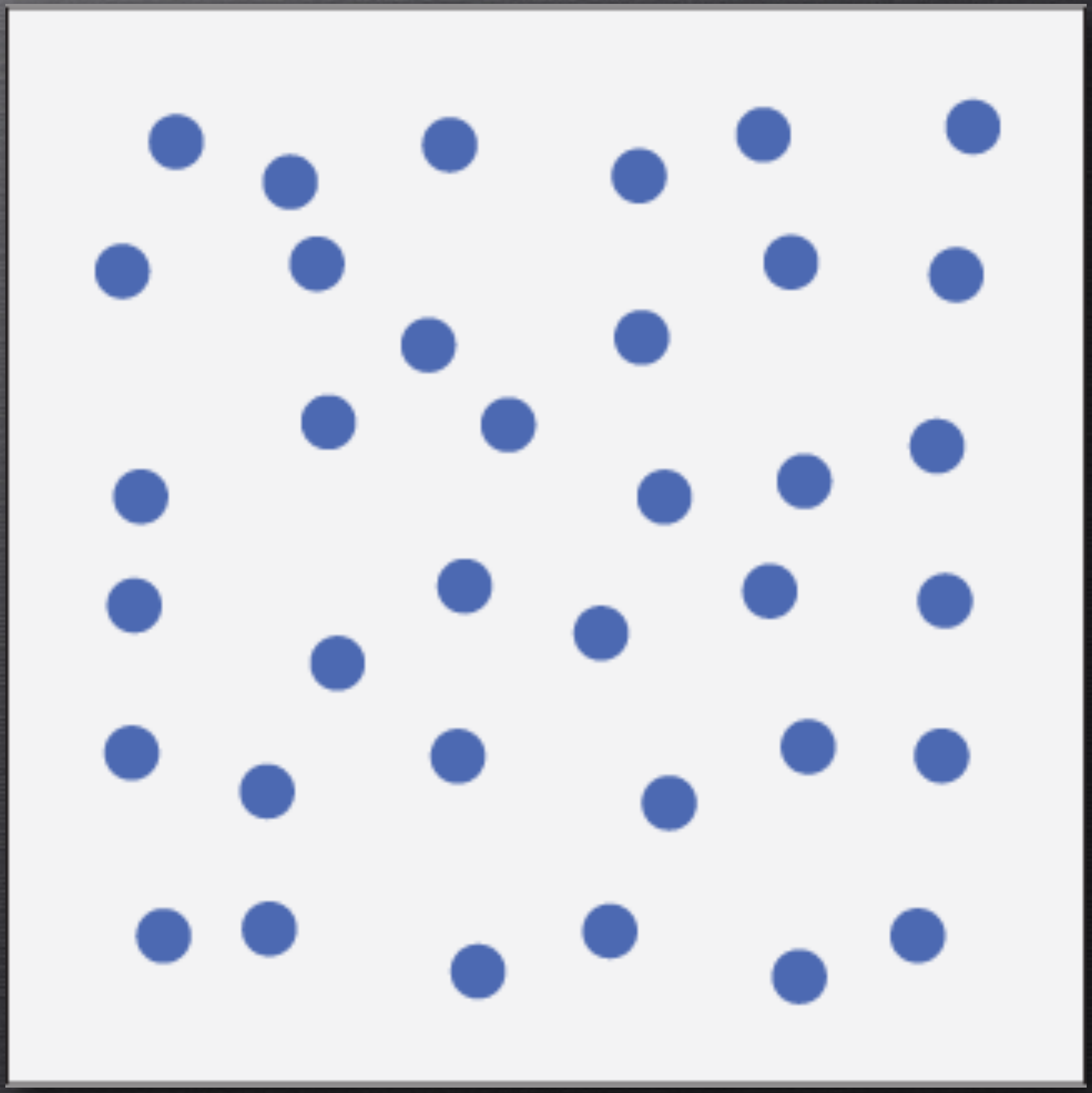
Present

www.csc.ncsu.edu/fauclty/healey/PP

Hue Target



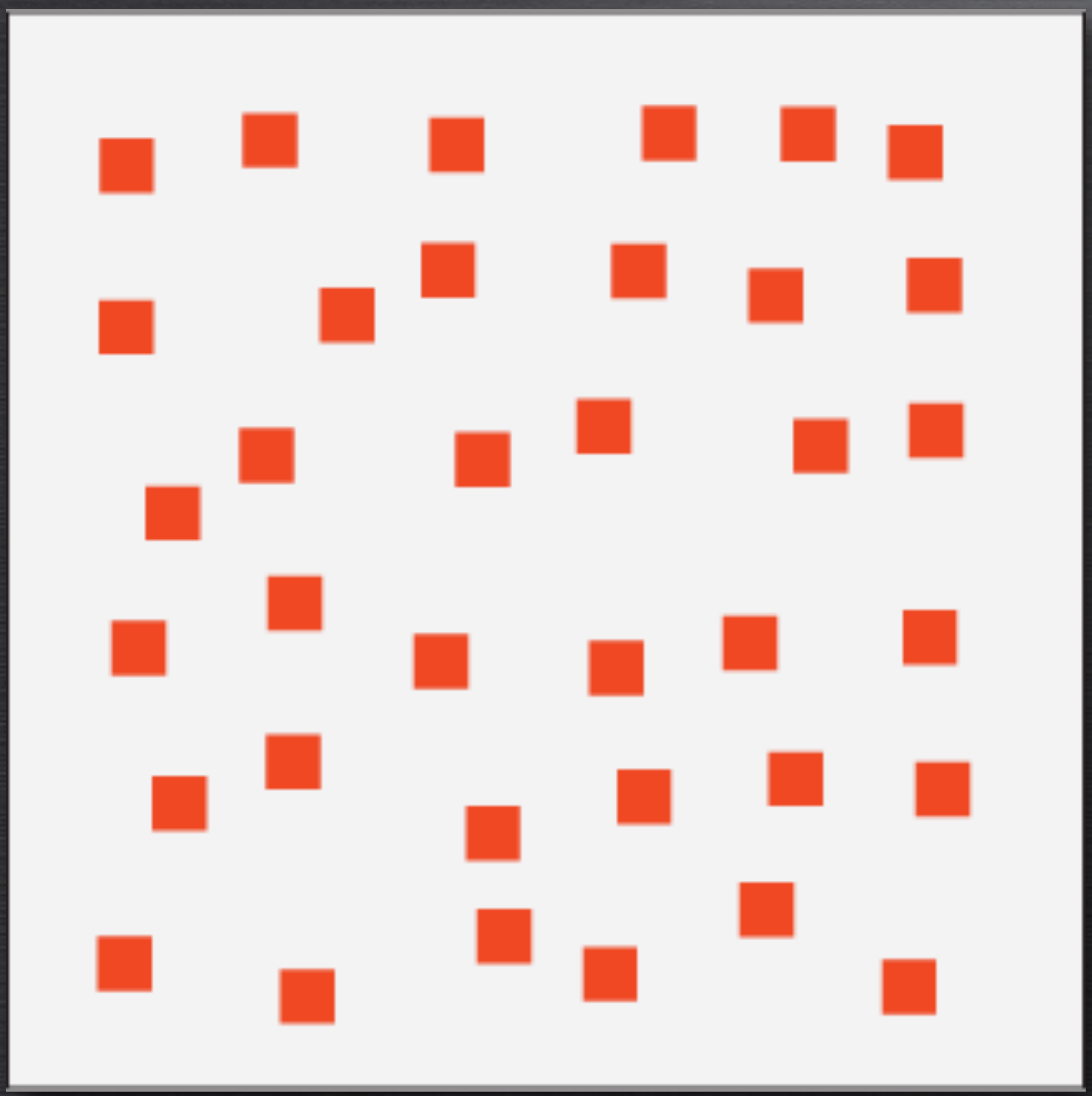
Present



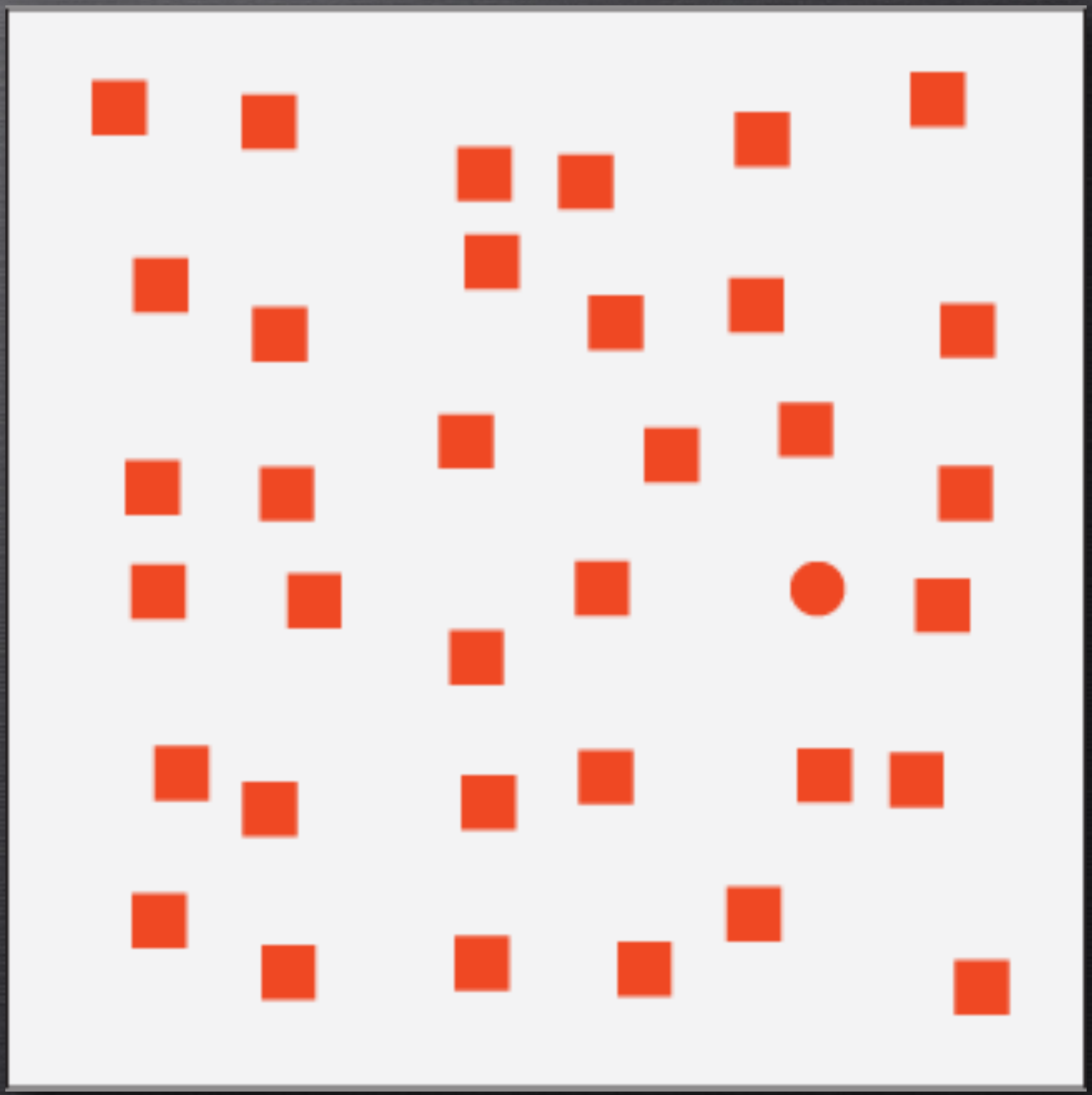
Absent

www.csc.ncsu.edu/fauclty/healey/PP

Curvature Target



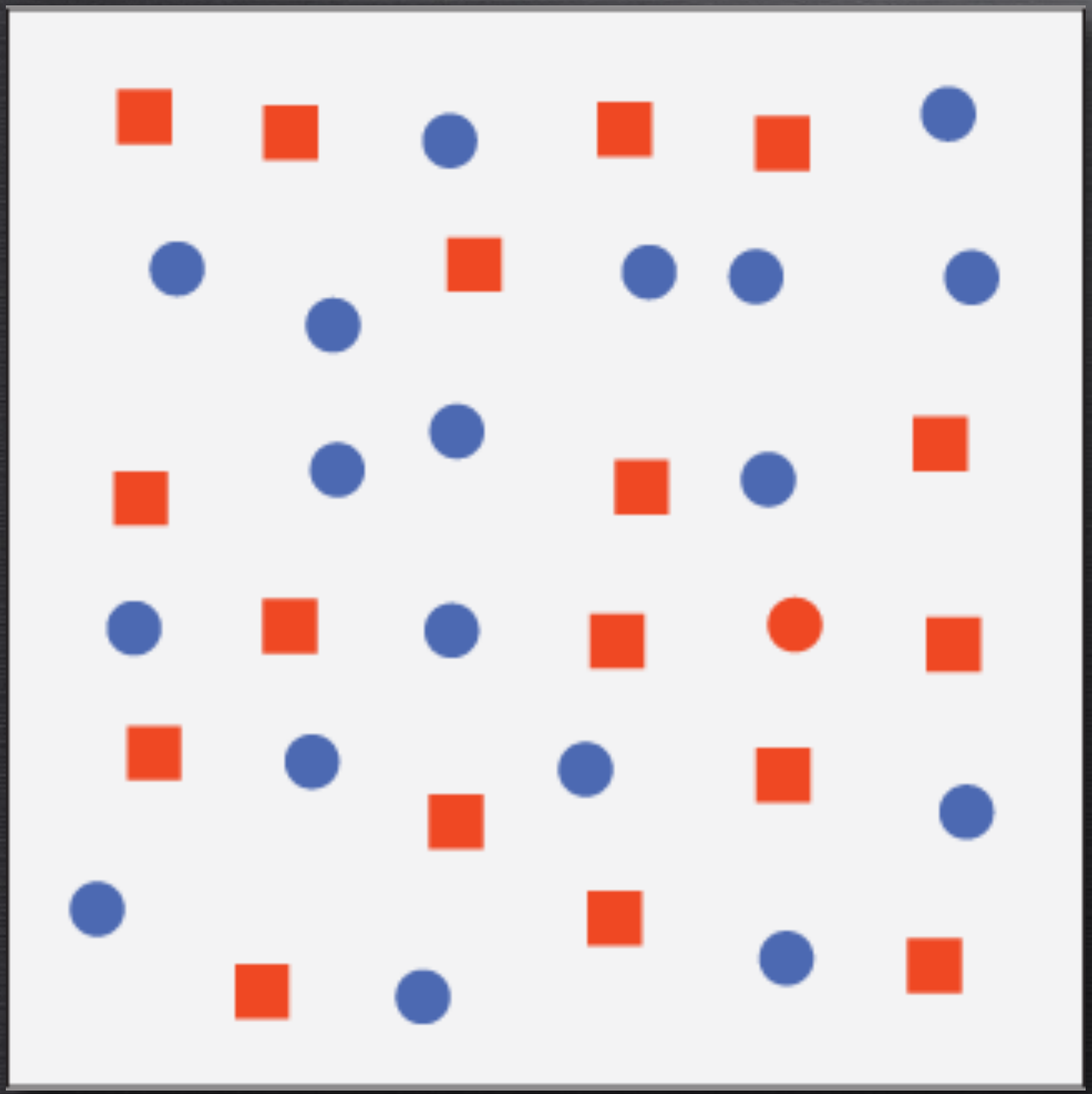
Absent



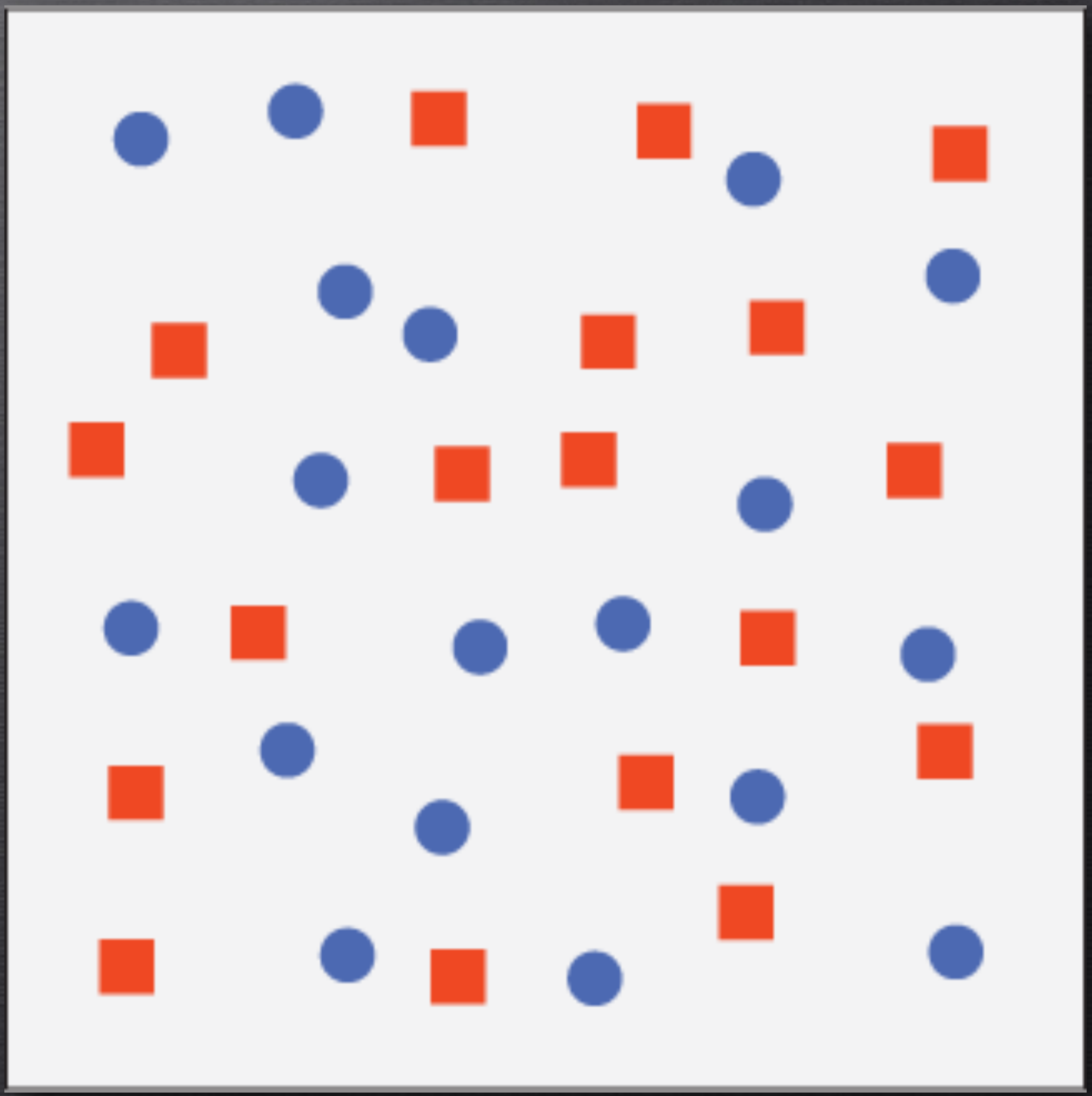
Present

www.csc.ncsu.edu/fauclty/healey/PP

Conjunction Target



Present



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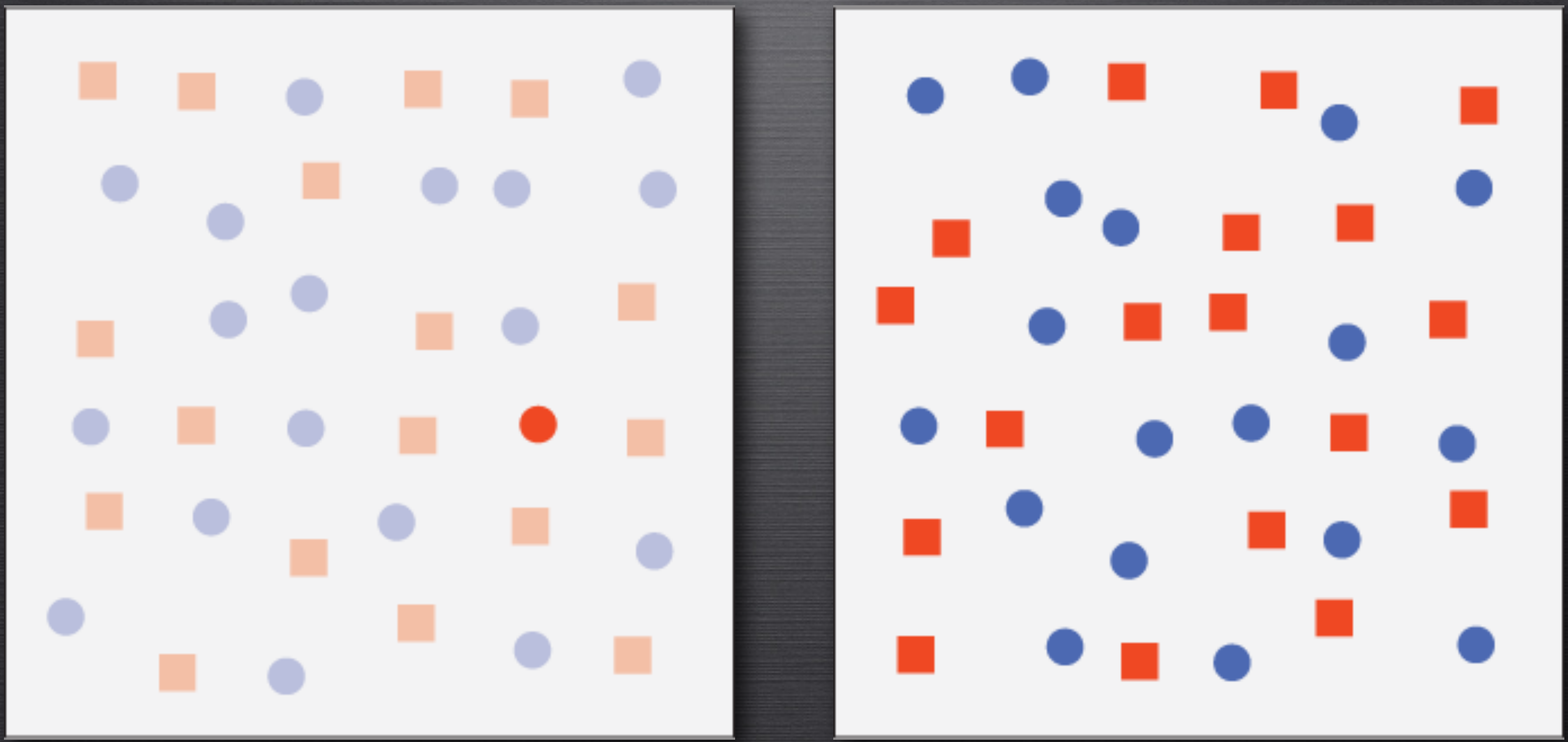


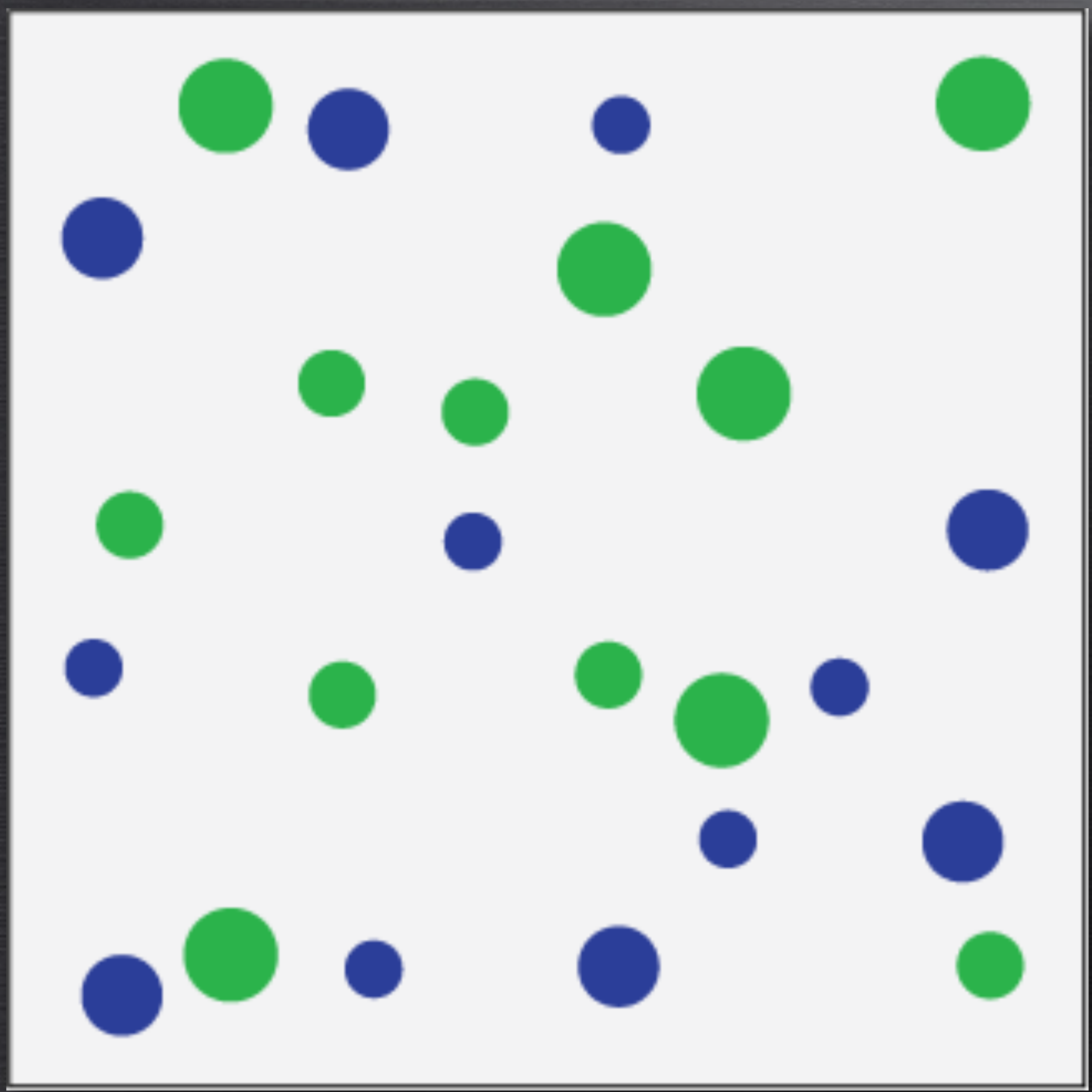
Present

Absent

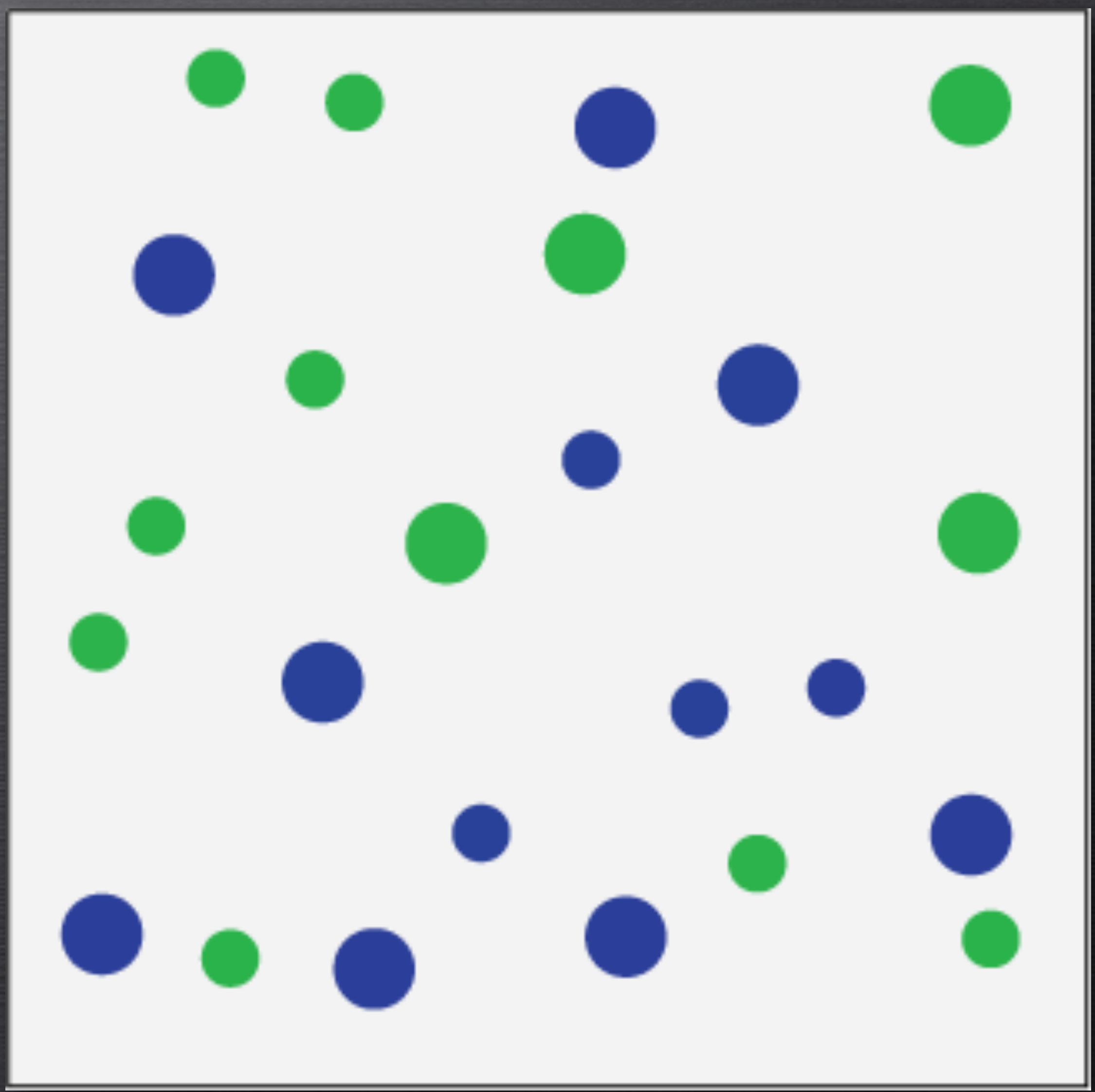
www.csc.ncsu.edu/fauclty/healey/PP

Ensemble Coding

Identify Which Colour has Larger Average Size



All Green Circles > All Blue Circles



More Large Blue Circles

Perceptual Guidelines

- Choice of data-feature mapping guided by knowledge of human visual perception
  - *Color:* hue, saturation, luminance, and/or chromaticity (hue + saturation)
  - *Texture:* size, orientation, density, regularity of placement
  - *Motion:* flicker, phase, direction, and velocity
- Feature "hierarchies" control order of data-feature mapping
- Luminance dominates hue, color dominates texture, regularity is perceptually weak, so:
  - most important data attributes are assigned to *luminance*,
  - then *hue* or *chroma*,
  - then *size*, *orientation*, or *density*,
  - then *regularity*

Postattentive Amnesia

- If viewers are allowed to preview a scene, will they be faster to answer questions about the details of the scene?
- Intuition suggest they will
  - Implies viewers have the ability to extract detail throughout a scene, access it rapidly on demand
- Various experiments have shown that human vision does not work in this manner
  - Vision is not a camera that can “snapshot” a full-detail representation of a scene
  - Results suggest that detail is only available at the most recent focus of attention

Priming Image

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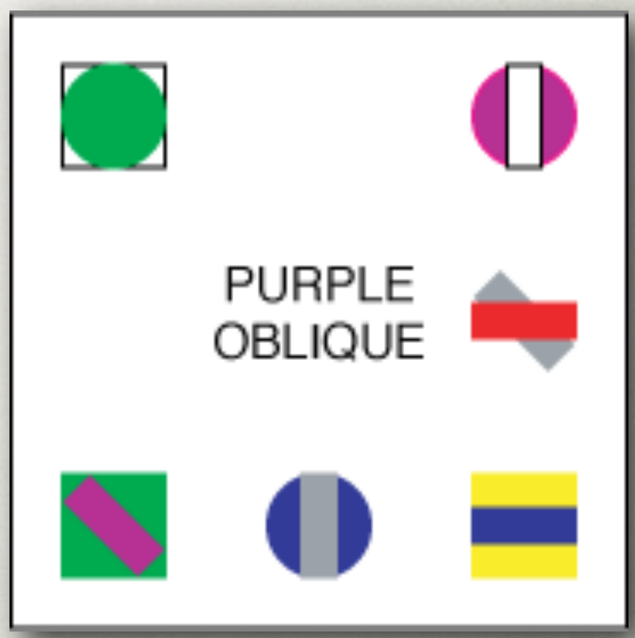
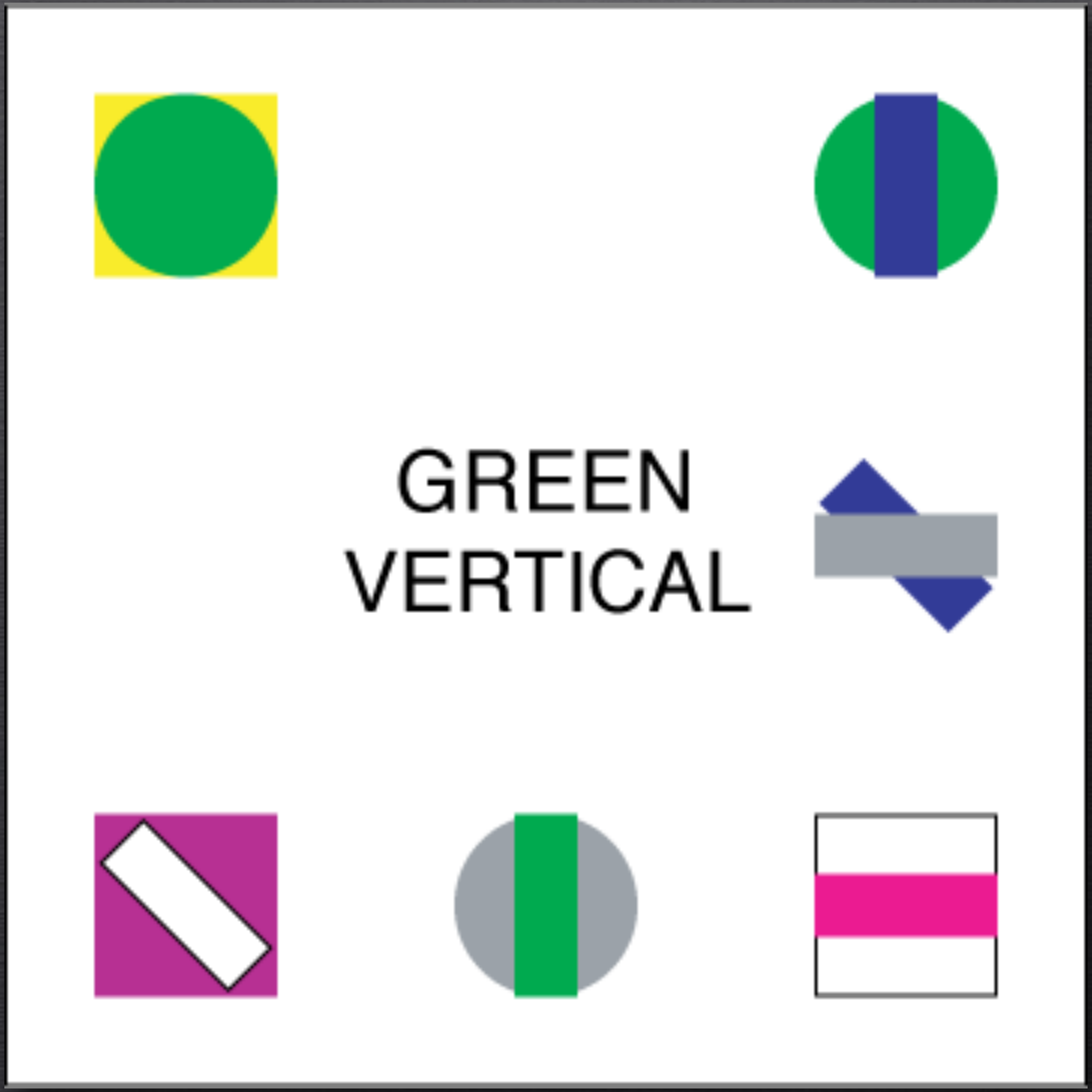


Search Image

Search With no Priming

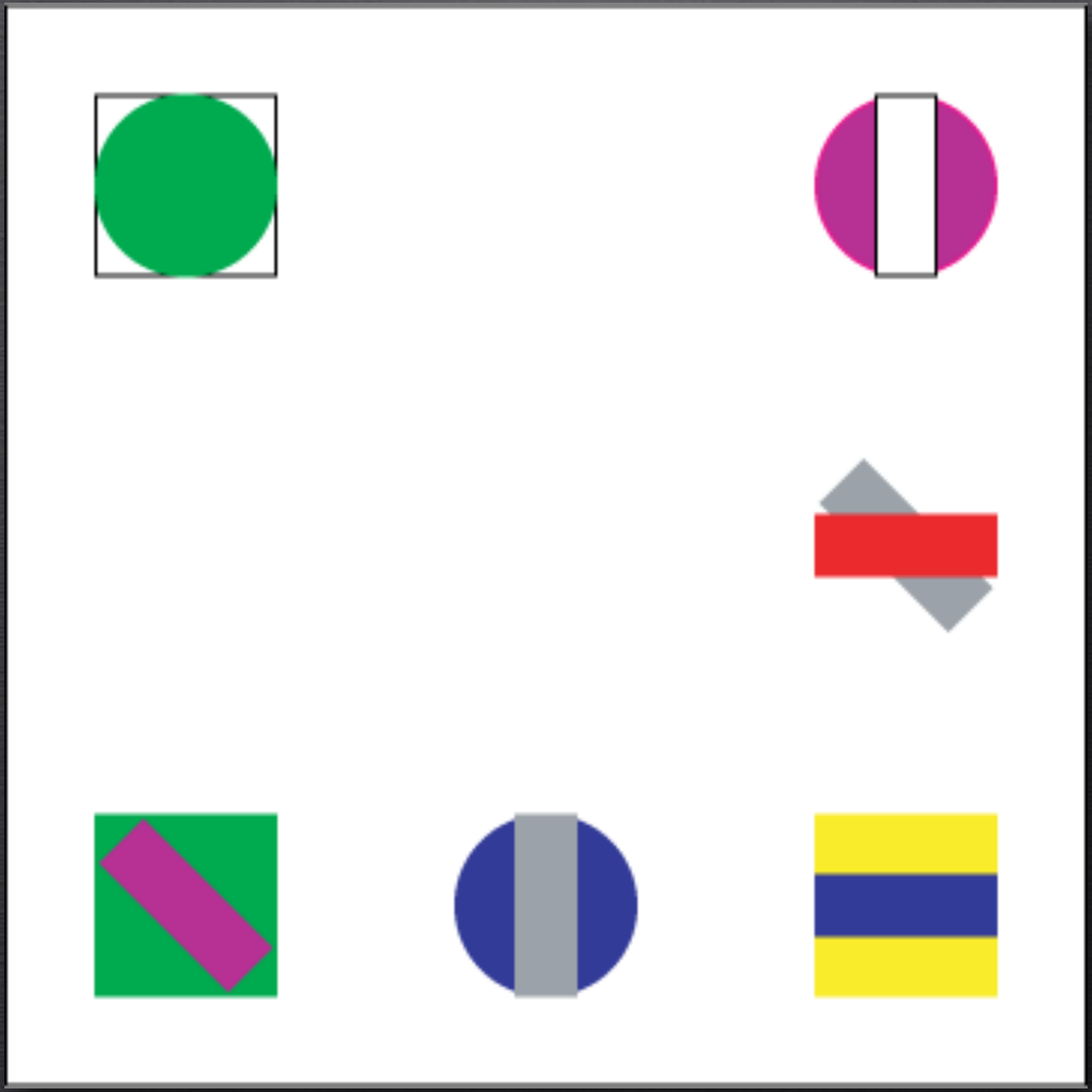
GREEN
VERTICAL

Search With no Priming

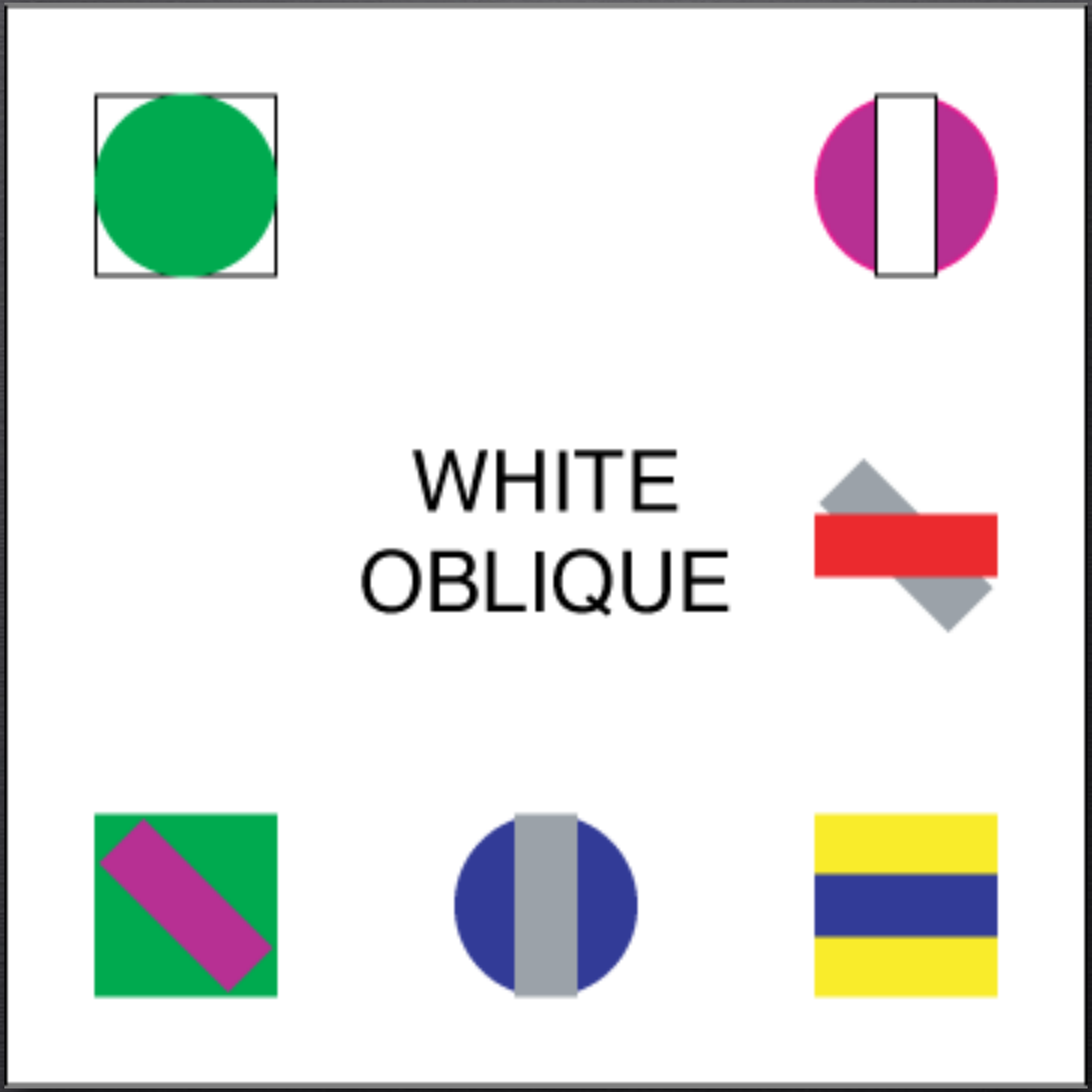


Present

Primed Search



Primed Search

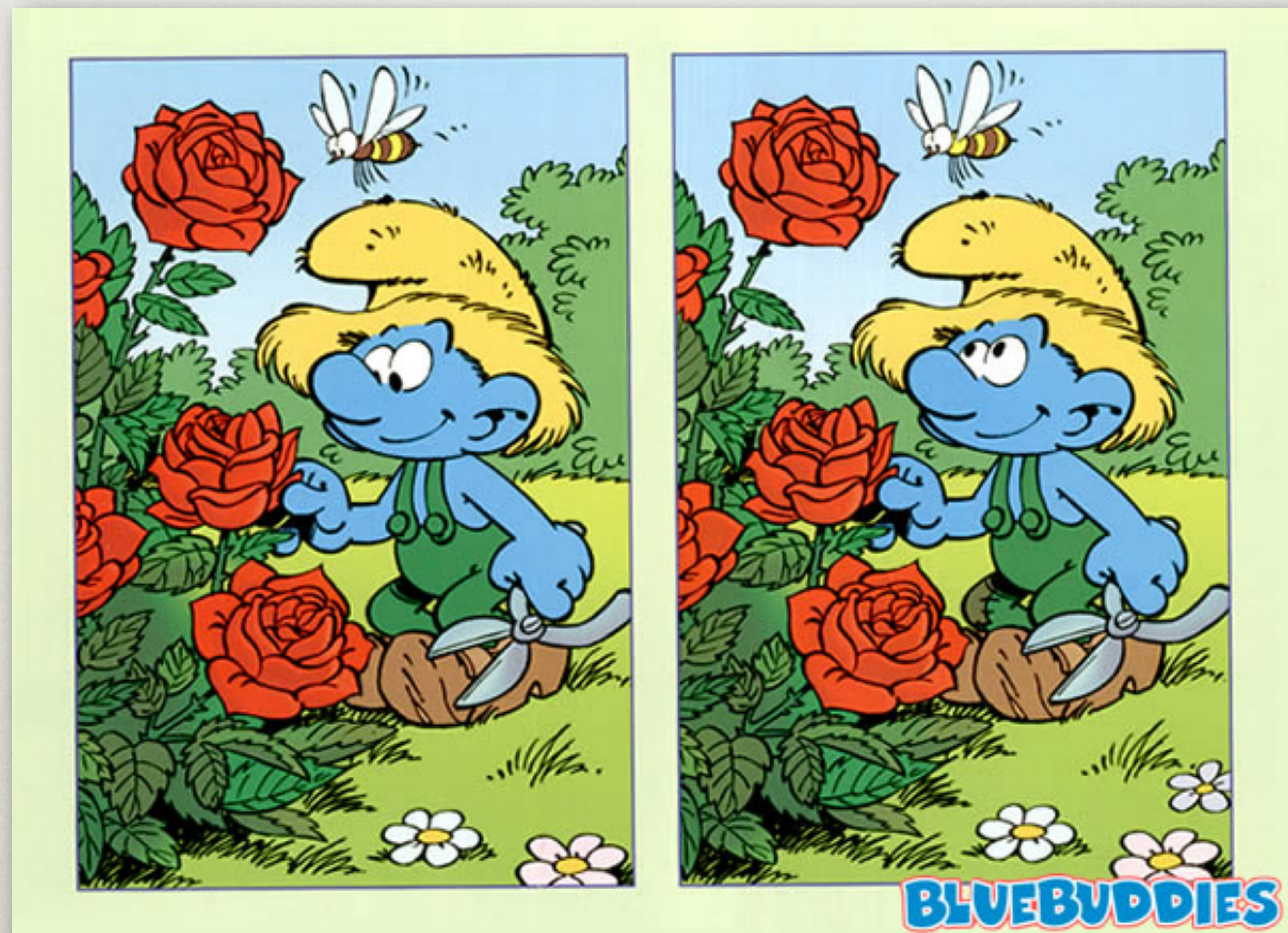


Absent

Change Blindness

- Visual system has limited memory for detail, often restricted to focus of attention
- Visual disruption (e.g., eye saccade) can render us “blind” to changes in a scene
- Example: find differences between two images
- Original research conducted at Nissan’s Cambridge Basic Research Centre
    - studying why accidents occur
    - significant visual evidence of a potential accident
    - sufficient time to avoid accident

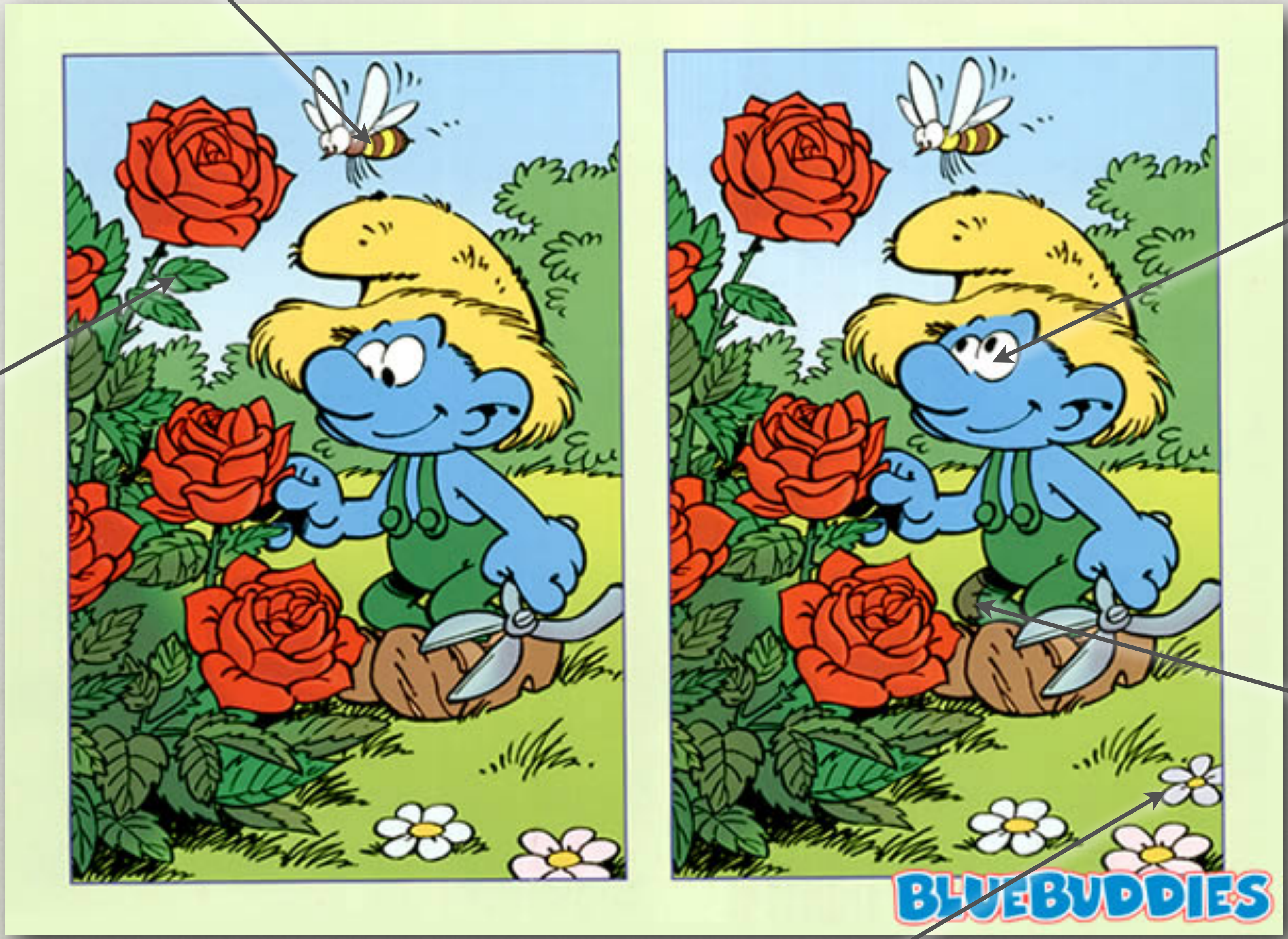
Find Five Differences



Find Five Differences

bee’s stripe colours reversed

eyes tilted up



extra leaf

patch on knee

extra flower

Change Blindness

Data courtesy Ron Rensink, Department of Psychology, UBC

Change Blindness

Data courtesy Ron Rensink, Department of Psychology, UBC

Change Blindness Models

- Overwriting
  - current image overwritten by new one
- First impression
  - initial view abstracted
- Nothing is stored
  - scene abstracted with no details
- Feature combination
  - previous and new views combined
- Everything is stored, nothing is compared
  - details cannot be accessed without external stimulus

Main actor changes across movie cut

http://www.icarus.ca/icarus/?p=1024

Okanagan Mountain Park Fire (Kelowna, BC, 2003)

64000 acres, $33.8 million,239 homes destroyed

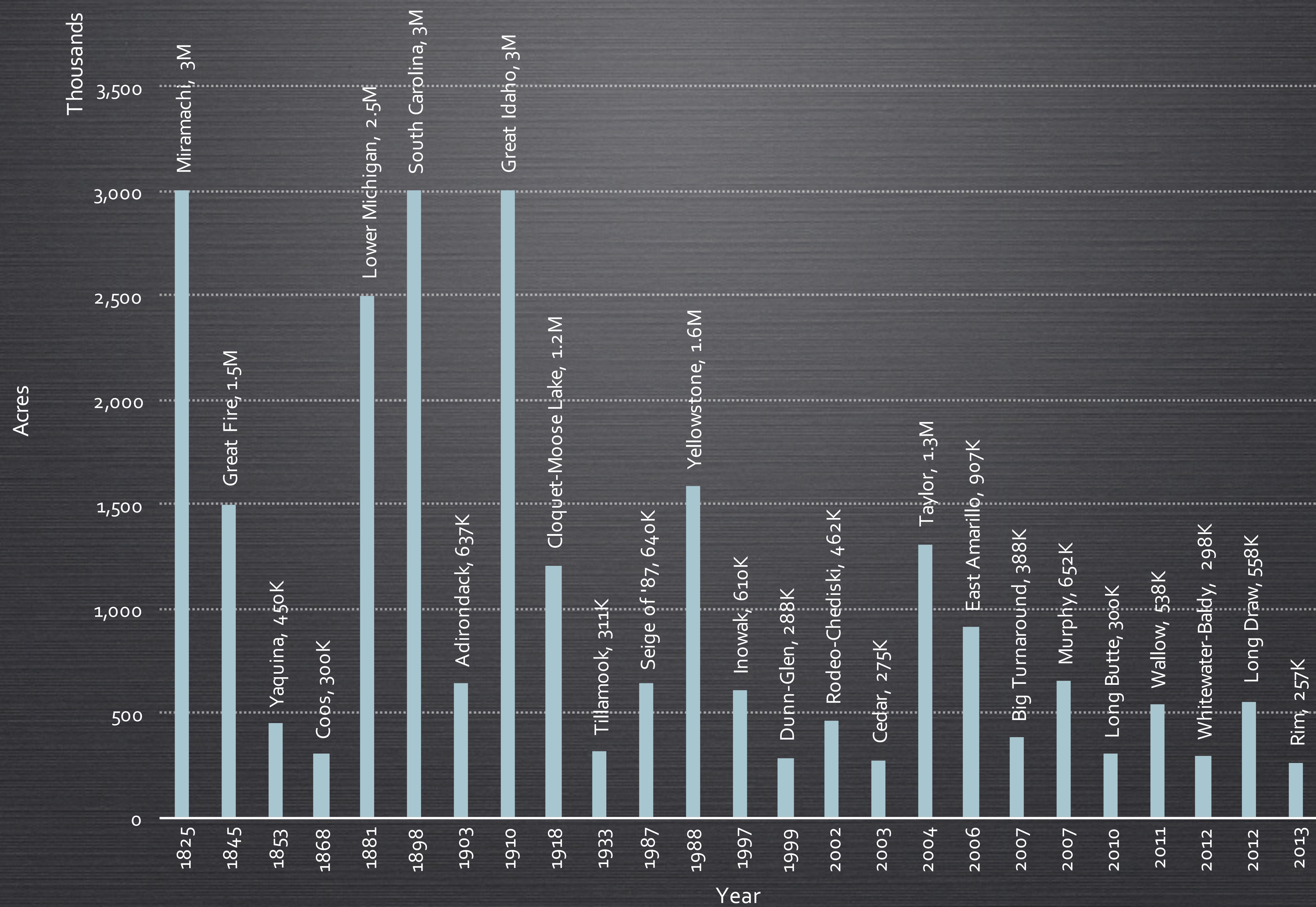
National Cohesive Strategy

To safely and effective extinguish fire, when needed;
use fire where allowable; manage our natural resources;
and as a Nation, live with wildland fire.

National Cohesive Wildland Fire Management Strategy
April, 2014

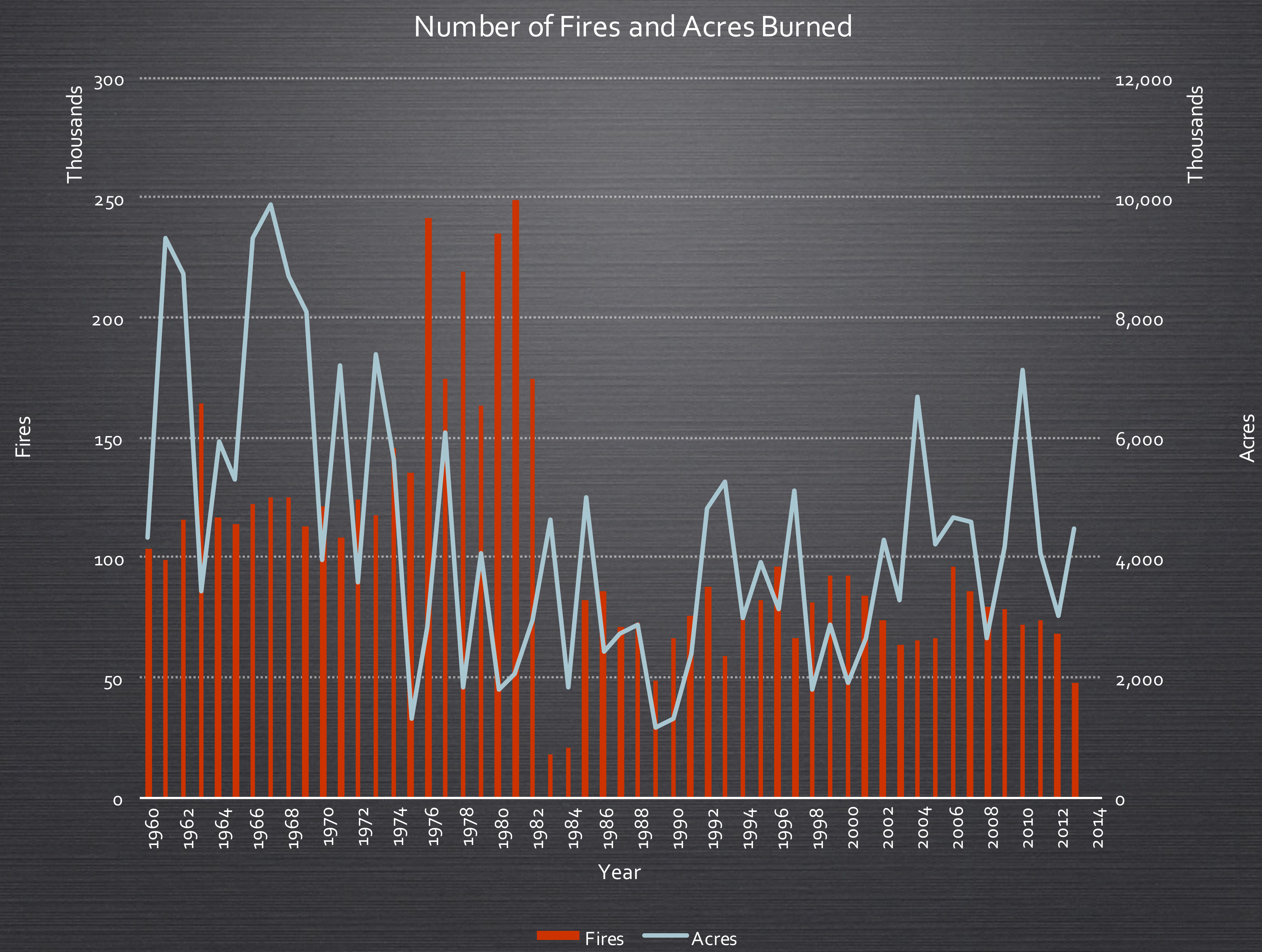
http://www.forestsandrangelands.gov/strategy

Twenty-Five Largest Fires By Acres



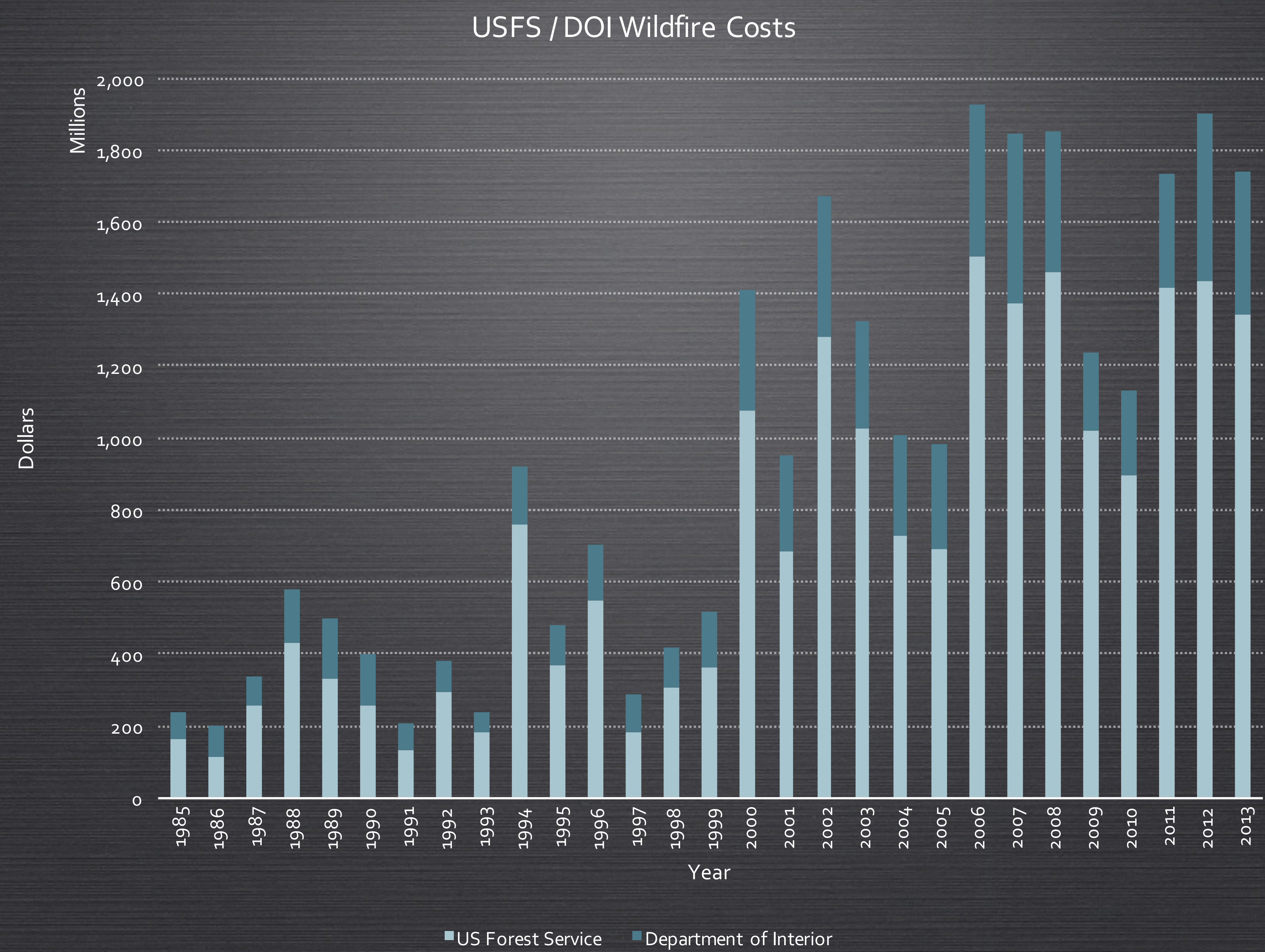
National Interagency Fire Center

http://www.nifc.gov/fireInfo/fireInfo_stats_histSigFires.html



National Interagency Fire Center

http://www.nifc.gov/fireInfo/fireInfo_stats_totalFires.html



National Interagency Fire Center

http://www.nifc.gov/fireInfo/SuppCosts.pdf

Project Objectives

- What are dominant wildfire and risk narratives communicated through social media?

- How are narratives shaped by ecological, social, and political characteristics?

- **Community Engagement:** Can fire officials communicate risk mitigation strategies via Twitter?

- **Communication:** Can Joint Fire Science monitor and communicate with a community during a wildfire event via Twitter?

WILDFIRE MITIGATION
Colorado Springs
Fire Department

Colorado Springs Fire Department Wildfire Mitigation

http://www.springsgov.com/Page.aspx?NavID=101

Project Plan

1. Capture, index, store wildfire incident Twitter communication
2. Perform thematic and sentiment analysis of tweets
3. Analyze and visualize information flow within social media networks

- **Community engagement:** for risk mitigation prior to a wildfire
- **Communication:** between emergency management and communities during wildfire events

Data Capture

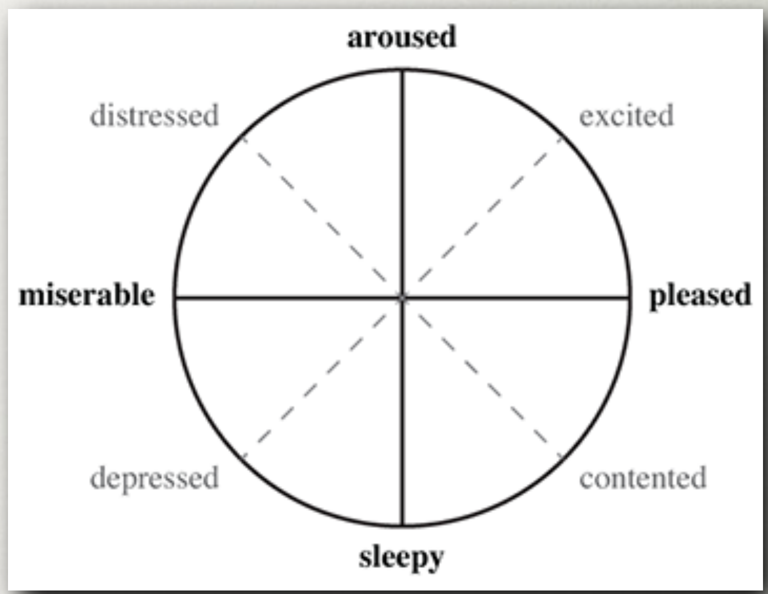
- Capturing tweets with keywords “wildfire” and “forest service” since May 14, 2013
    - 5.3 million tweets stored in MySQL database
- Extracting relevant tweet properties
    - date and time
    - author
    - body
    - geolocation
- `DenverCP | -104.994593,39.746012 | Wildfire burning SW of Beulah closes Hwy. 165: BEULAH, Colo. A small wildfire burned in Pueblo County just... http://t.co/FfPeLrpIS6 | Sun Jun 01 02:21:12 +0000 2014`

Sentiment

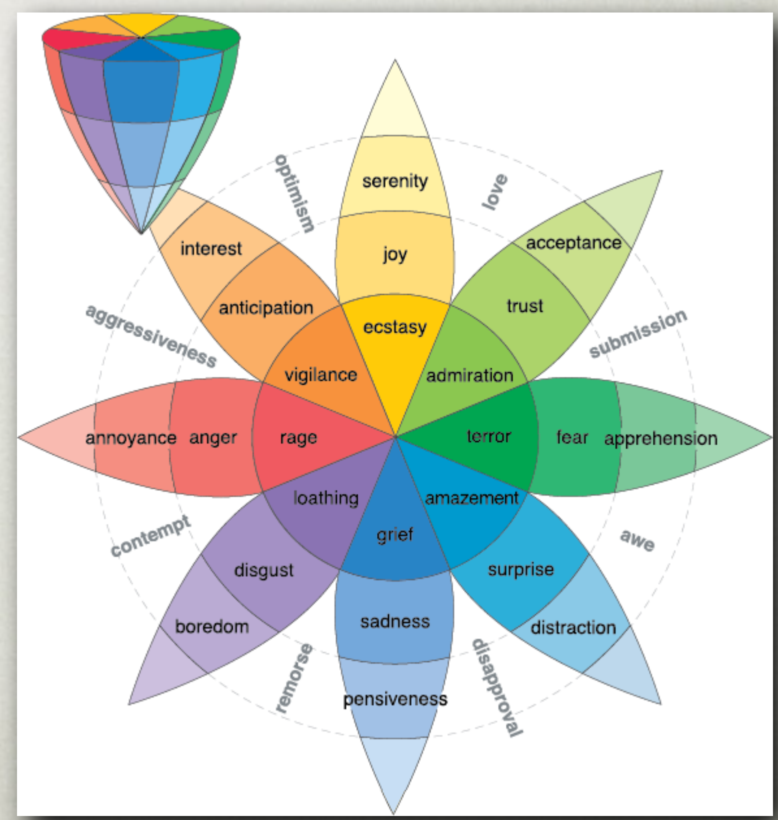
- "An attitude, thought, or judgment prompted by feeling"
- Natural language processing (NLP) approaches
  - Subjectivity classification, machine learning, semantic orientation
- Sentiment dictionaries
  - **Profile of mood states (POMS):** tension–anxiety, depression–dejection, anger–hostility, fatigue–inertia, vigor–activity, confusion–bewilderment
  - **Affective Norms for English Words (ANEW):** valence, arousal, dominance
  - **SentiStrength:** 298 positive terms, 465 negative terms, support for social network text
  - **SentiWordNet:** Sentiment scores for WordNet synsets

Emotional Models

- Psychological models of emotion
  - Russell's emotional circumplex: orthogonal valence and arousal axes
- Emotional scatterplot
  - 2D scatterplot, valence and arousal as horizontal and vertical axes
  - Intermediate regions: upset, stressed, nervous, tense
- Similar alternative models
  - Plutchik's eight bipolar dimensions
  - Thayer's tense–calm, tired–energy model



Russell's circumplex



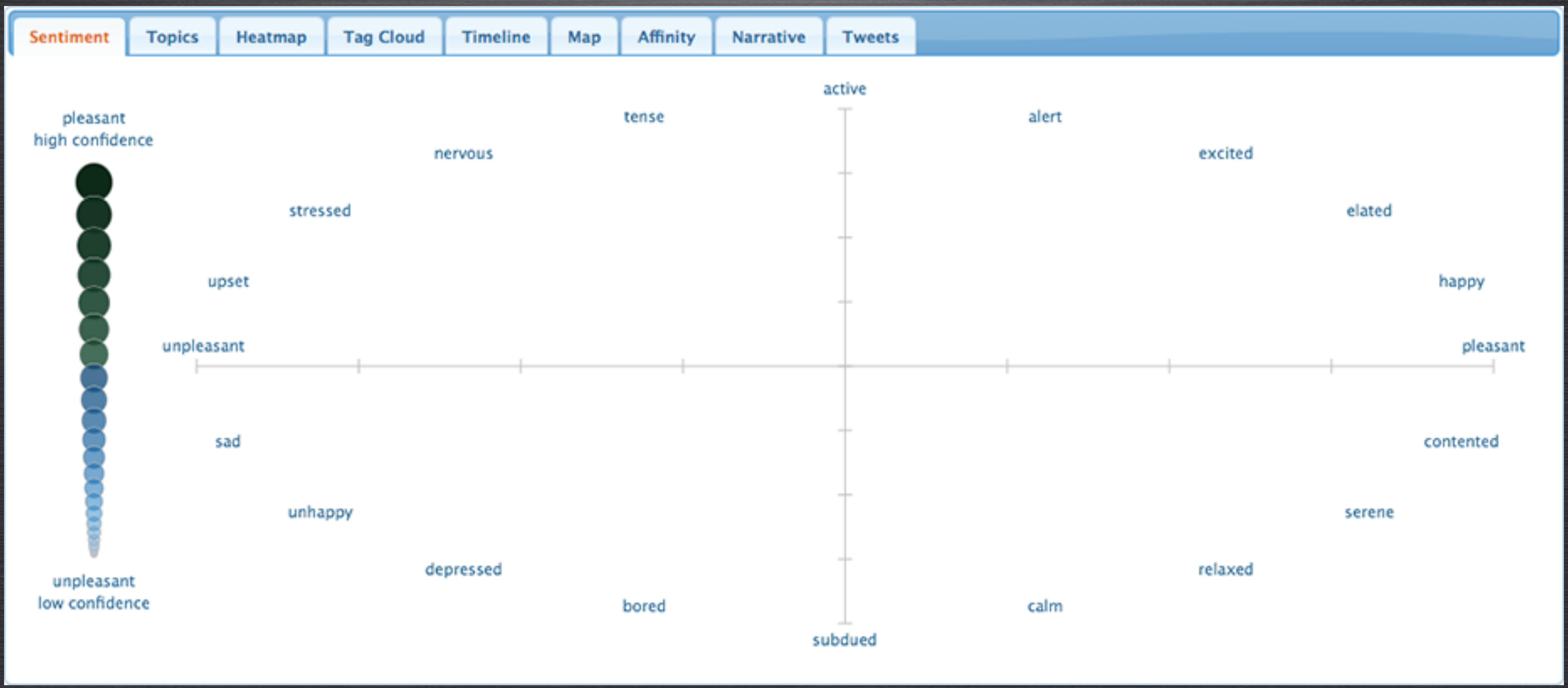
Plutchik's emotion wheel

Recent Tweet Visualizer

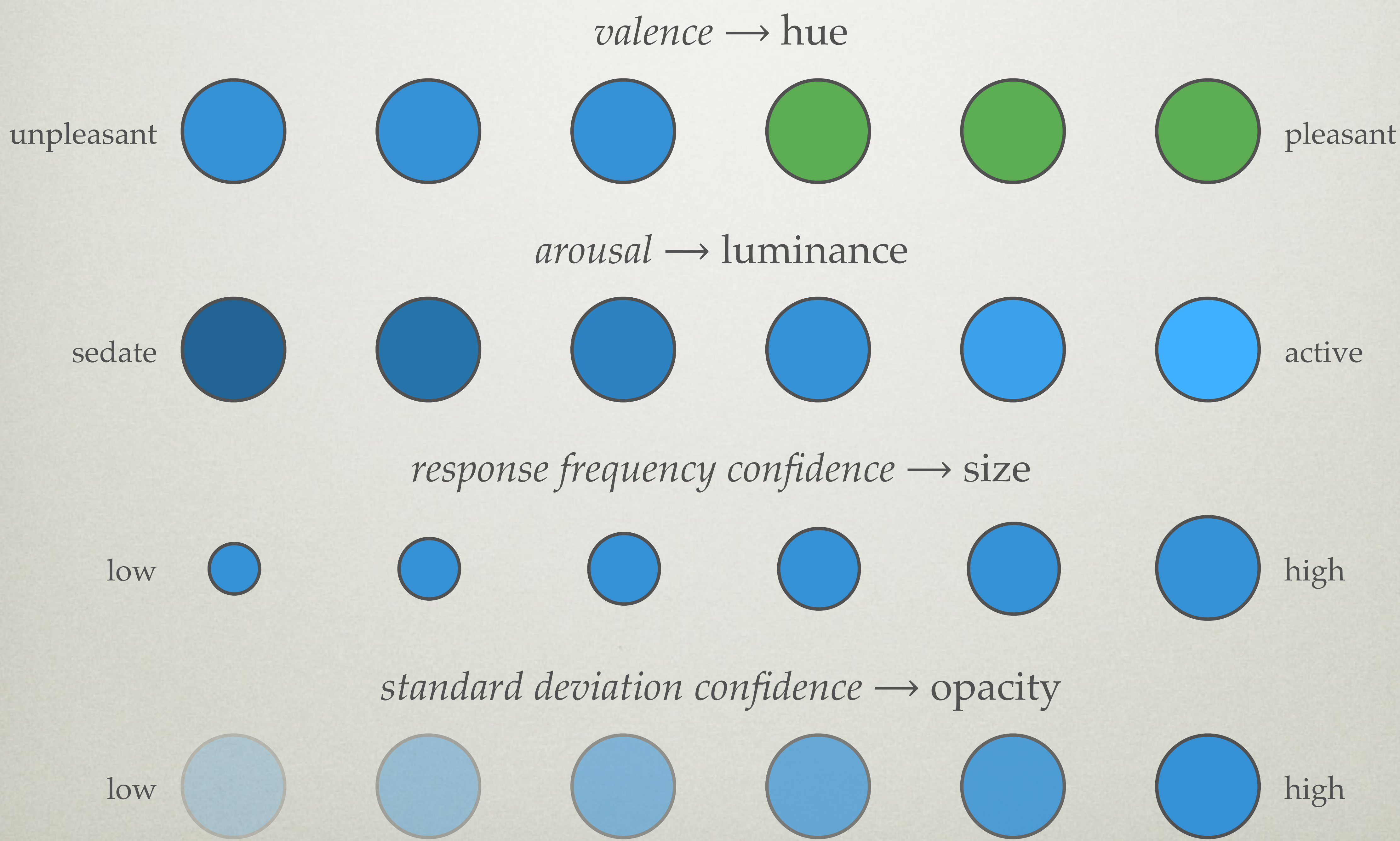
- Visualize "recent" tweets that match user-chosen keywords
  - Twitter API supports keyword searches in the recent tweet pool

1. Allow users to enter keyword search string
2. Query Twitter for recent tweets matching keywords
3. Identify tweets with at least n=2 dictionary terms
4. Estimate the sentiment of each tweet
5. Visualize tweets on an emotional scatterplot
   - Map valence and arousal to hue and luminance
   - Map two measures of confidence to size and opacity

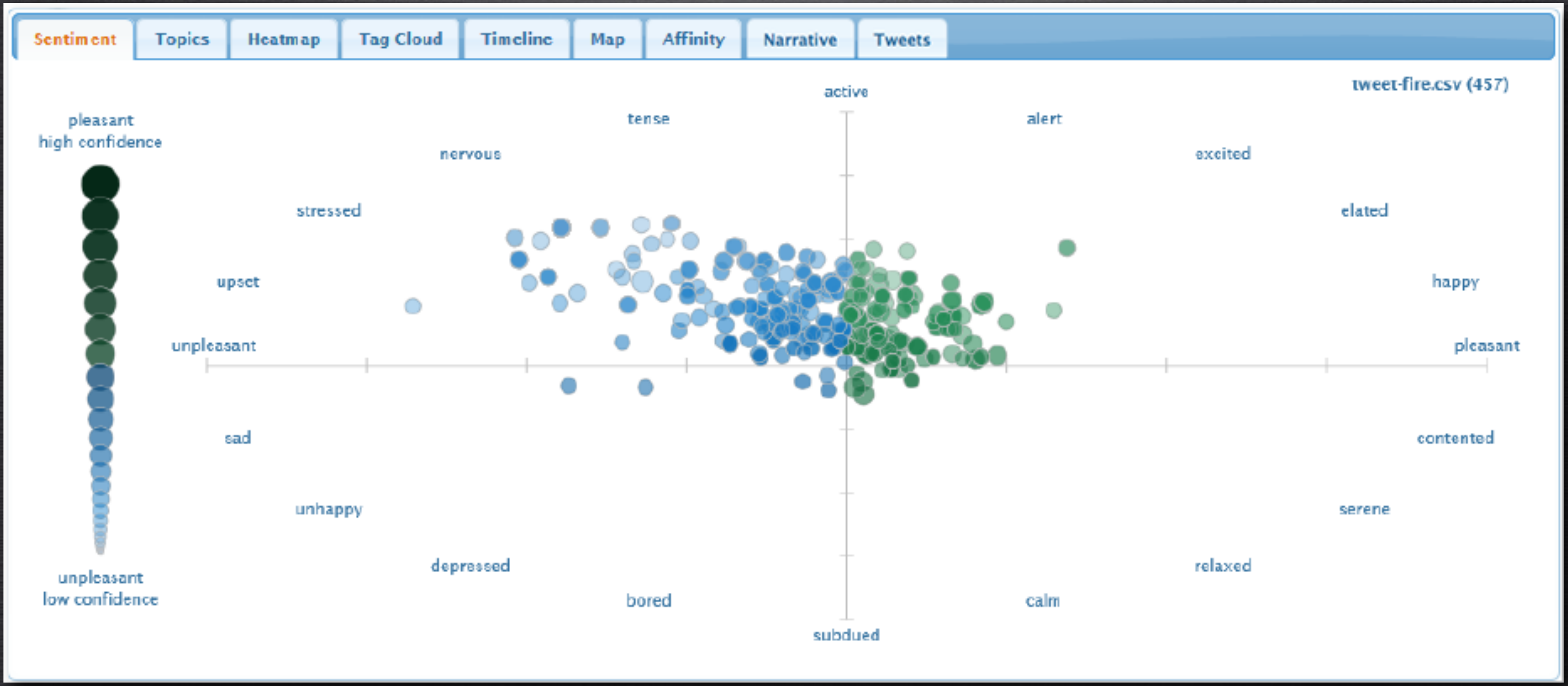
Emotional Scatterplot



Tweet Glyphs



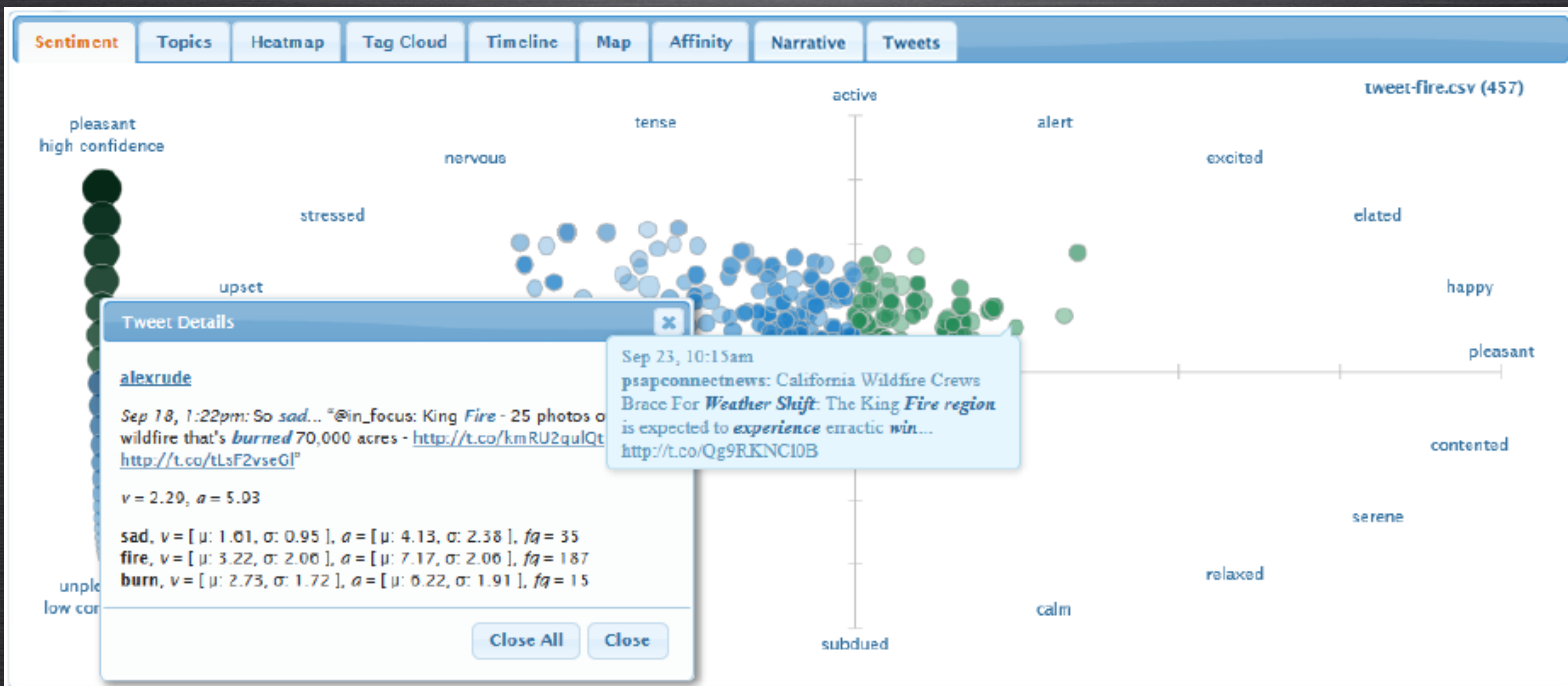
Sentiment Scatterplot



King Fire (El Dorado County, CA, 2014)

97717 acres, $91 million, 80 residences destroyed

Sentiment Values



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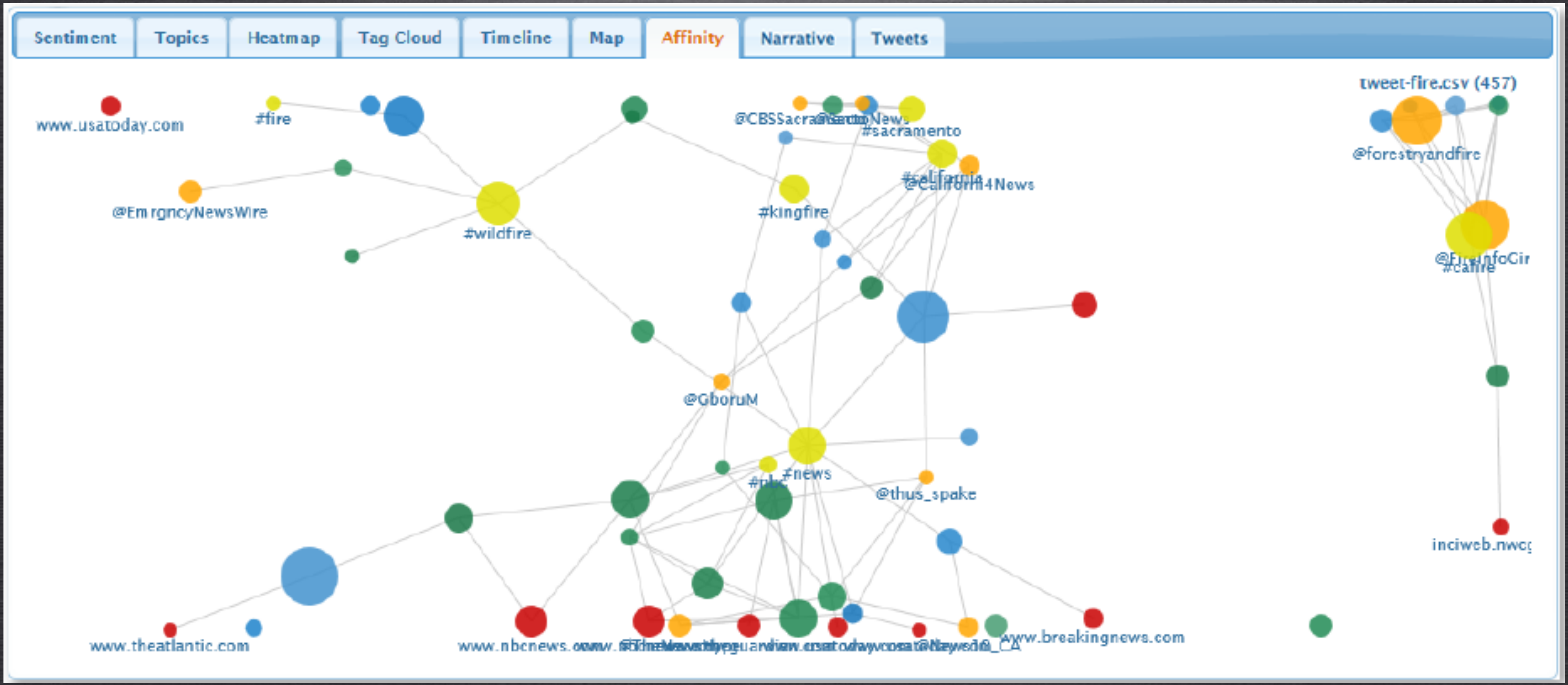
Affinity Graph



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Conclusions

- Text visualization has matured
  - Numerous techniques tailored to specific text properties
  - Focus on analytics for analyzing massive data collections prior to visualization
  - Focus on deriving useful properties from text
- Sentiment analysis continues as an active research area
  - Multiple approaches, depending on text type
  - Unresolved challenges: negation, context, subject identification, sarcasm
- Text analytics coupled with visualization can provide useful insights
  - Environmental risk management and tracking
  - Political trend analysis

Tweet Visualizer Demonstration

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Fire chasers Project

research.cnr.ncsu.edu/blogs/firechasers

Tweet Visualizer

www.csc.ncsu.edu/faculty/healey/
tweet_viz/tweet_app

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